ABSTRACT

Title of Thesis:	SPATIAL DISTRIBUTION OF SURFACE SOIL MOISTURE UNDER A CORNFIELD.
	Jackson K Fisher, Master of Science, 2004
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Autocorrelation within surface soil moisture (SSM) data may be used to produce high-resolution spatial maps of SSM from point samples. The objective of this study was to characterize the temporal and spatial properties of SSM (0-5 cm) in a Beltsville, MD cornfield using a capacitance probe. The range of spatial autocorrelation was approximately 10 m and the highest sill values were found at water contents (θ) between 20-27%. Nugget values represented a significant portion of the total variance (up to 50% for $\theta > 20\%$ and 73% for $\theta < 12\%$). The patterns of SSM under wet conditions exhibited large, continuous polygons while drier conditions resulted in smaller, discreet regions. Early season (< 60 days) Auto-Regressive Moving-Average (ARMA) forecasts of SSM plotted against observed data resulted in R^2 values from 0.15-0.26, while late season (> 80 days) forecasts improved to 0.46-0.65. Forecasts were improved by autoregressive coefficients and additional SSM datasets.

SPATIAL DISTRIBUTION OF SURFACE SOIL MOISTURE UNDER A CORNFIELD.

By

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DEDICATION

To my friends and family; may you spend many hours reading and enjoying this work

ACKNOWLEDGEMENTS.

I would like to take this opportunity to thank my committee and my co-workers for their efforts in completing this project.

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INTRODUCTION

A primary goal of a precision agriculture system is to effectively manage crop variability. Within a field, there tend to be certain components and processes that will significantly impact the variability of crop production. Runge and Hons (1998) discussed the hierarchical structure of the different variables affecting crop yield and found that water, in the form of rainfall and plant available stored soil moisture, caused most of the temporal and spatial differences in yield.

Unfortunately, spatial measurements of soil moisture at within-field scales are rarely available. Typically, soil moisture measurements are conducted as point measurements or as large area (>1000 m^2) measurements (Grayson et al; 1998). Characterizing soil moisture in a small area or field requires high-resolution remote sensing technology and/or significant amounts of point measurements. In both cases, the costs associated with acquiring the data are very high; and thus, it makes this level of sampling impractical in most situations.

Compounding the problem is the fact that measurements of soil moisture will also vary throughout the season. Rainfall, evaporation, and plant transpiration are all examples of processes that impact the levels of soil moisture over time. Although monitoring systems can be set up to record seasonal information on soil moisture, the densities of these measurements tend to be low. Characterizing soil moisture in spatial areas over time can be a significant problem for precision agriculture.

Due to the impact that soil moisture has on the yield of a crop, a greater understanding and ability to determine the small scale, spatial distributions of soil moisture throughout the growing season would greatly assist in the management of a

precision agriculture system. Therefore, the focus of the following discussion will be on improving the small scale surface moisture data available for precision agriculture management by understanding and characterizing the spatial soil moisture processes that occur within small areas of a cornfield during the growing season.

LITERATURE REVIEW

AUTOCORRELATION

Managing variability in agricultural field studies is challenging because of the relationships that exist between variables. Soil properties, water distribution, crop attributes, and location are all examples of variables found within an agricultural management system. When studying the response of the system to environmental or managerial changes, the impact of any one of these variables can become quite difficult to separate. In most agricultural studies, observed variables in field studies are collected using sampling schemes that try to account for correlations that exist within or between variables (Fagroud and Meirvenne, 2002; Van Es and Van Es, 1993). In general, closer observations tend to be more related than observations separated by great distances. For temporal measurements, observations repeated in a short time interval tend to be more related than observations separated by long periods of time. Blocking, repetitive sampling, and multi-variate observations are all methods used to determine and account for relationships that occur within sets of sampled variables. Relationships that exist within and between sampled variables can significantly impact the statistical analysis of a study and, therefore, should be quantified to ensure that accurate information is used when the study's conclusions are determined.

Autocorrelation is a specific type of correlation that exists between neighboring observations of a single variable. Spatial and temporal spacing is a significant factor contributing to the amount of autocorrelation found within a variable. Precision agriculture systems, which are made up of layers of spatial information that are combined to make management decisions, typically have repetitive samples over short periods of time or distance, These systems often produce datasets that contain significant autocorrelations. The level of autocorrelation found in a variable is characterized by the autocorrelation coefficient.

The autocorrelation coefficient is defined as the amount by which an observation is linearly related to another neighboring observation. The autocorrelation coefficient is a combination of a covariance function and a variance function. The autocorrelation coefficient, r(h), is calculated in the following way:

$$\text{cov}\left[A_i(x), A_i(x+h)\right] = \frac{1}{N} \sum_{i=1}^{N-h} \left[A_i(x_i) - \overline{A}\right]\left[A_i(x_i + h) - \overline{A}\right]$$

$$\text{var} = s^2 = \frac{1}{n} \sum_{i=1}^{n} \left(z_i - \overline{z}\right)^2$$

$$\text{r}(h) = \frac{\text{cov}\left[A_i(x), A_i(x+h)\right]}{\sqrt{\text{var}\left[A_i(x)\right]}\sqrt{\text{var}\left[A_i(x+h)\right]}}$$

(Nielsen and Wendroth; 2003)

As the autocorrelation coefficient approaches zero, the observed variable is considered to be unrelated to previous or neighboring observations. By plotting the changes in the autocorrelation coefficient over time or against the distance between

observations, an autocorrelation function or correlogram can be derived. An autocorrelation function can be used to describe the change in dependence between individual samples within a set of observations. By studying the spatial and temporal autocorrelations in different variables of the system, a better understanding of the dynamics of the system can be achieved.

The autocorrelation present in an observed variable is related to the underlying processes of the variable (Nielsen and Wendroth; 2003). In agricultural field studies, there are a wide range of variables that cover all aspects of the crop, soil, and weather. Numerous studies have been conducted to investigate the autocorrelation that are characteristically associated with different soil variables (Li et al, 2002; Cassel et al, 2000; Greminger and Nielsen, 1985). Soil texture, organic material, nutrient concentrations, and soil moisture levels are examples of some of the soil-based properties that have been studied. Field studies involving autocorrelated variables have focused on spatial changes that occur between different areas of the field as well as temporal changes that occur between seasons or sampling intervals. The variability of soil properties and the impact that these properties have on crop production and sampling strategies are reasons to study how the autocorrelation coefficients and functions could be used to explain a portion of the variability in the field.

SEMI-VARIOGRAMS

The semi-variogram is a basic geostatistical tool used to describe the changes in the variance at different distances between observations (Isaaks and Srivastava, 1989).

The equation for semi-variance ($\gamma(h)$) is:

$$y(h) = \frac{1}{2} N(h) \sum_{i=1}^{n} [A_i(x_i) - A_i(x_i + h)]^2$$

(Nielsen and Wendroth; 2003)

where $A_i(x_i)$ and $A_i(x_i + h)$ are experimental measures of any two points separated by the vector h (lag distance), N equals the number of pairs of points, and x is a location vector.

The semi-variogram can vary depending on the sampling interval defined by vector h, also known as the lag distance. The lag distance defines the number of pairs of points that are present in each sampling interval. In general, closely spaced samples use smaller lag distances, while widely spaced samples use longer lags. Lag distance, however, is determined not only by sample spacing but also by the number of pairs of points in each lag interval. A balanced distribution of point pairs across the sampling range is ideal for semi-variogram calculations. A basic non-directional or omni-directional semi-variogram uses a 360-degree sampling region to find points within a lag distance. Depending on the type of data or orientation of the sampling, a directional search area can be defined using a directional vector and a search angle. In these cases, only the points falling within the search area are used to calculate the semi-variogram. Semi-variograms are a common method used to characterize spatial autocorrelation within agricultural studies.

Several sampling strategies have been used to characterize the sample semi-variogram. Equal spaced measurements on a regular grid are one of the most common strategies used in field studies that investigate spatial patterns (Solie et al., 1999; Hupet and Vanclooster 2002; Ferreyra et al, 2002). This method is quite

effective but can be considered an inefficient use of resources. The regular grid sampling scheme will result in a skewed number of observation pairs at short lag distances compared to the numbers of pairs at longer sampling lags. A nested set of samples is one way to produce a more even distribution of samples (Cahn et al 1994; Fagroud et al 2002; Tomer et al, 1995). In this method, the sample locations are not consistently spaced. Some of the nested methods use a combination of multiple grid patterns at different scales while others use a combination of a regular grid pattern with additional randomly selected locations. In either case, the nested sampling method produces a more balanced number of pairs at short and long lag lengths. With limited resources, this method is a more efficient way to acquire the sample semi-variogram (Russo, 1984). The regular grid and the nested sampling pattern are both considered acceptable methods to acquire the sample semi-variogram.

Once the sample semi-variogram has been calculated, the next step is to model how the variance of the sample semi-variogram changes over time using a theoretical semi-variogram model. The theoretical semi-variogram model is defined by three main components: the nugget, sill, and range (Figure 1). The nugget value is defined by the y-intercept of the semi-variogram. The magnitude of the nugget is associated with the random or non-structured variability of the observed process. Observations that are highly repeatable (low random variation) will have lower nugget values. Rapidly changing conditions or instrument variation could cause higher random errors and a higher nugget value. Nugget values may increase because of structured variations that occur at distances smaller that the sample spacing. By decreasing the sample spacing, these variations may be removed from the nugget.

The sill is the maximum variance determined by the semi-variogram and represents the total amount of variance present in the system. The distance at which the semi-variogram reaches the sill is defined as the range. The range is the maximum distance that the observations display correlation. At distances greater than the range, observations are considered to be independent and random. The theoretical models are classified into broad categories based on the rate of change of the nugget, sill, and range.

Components of a Semi-Variogram
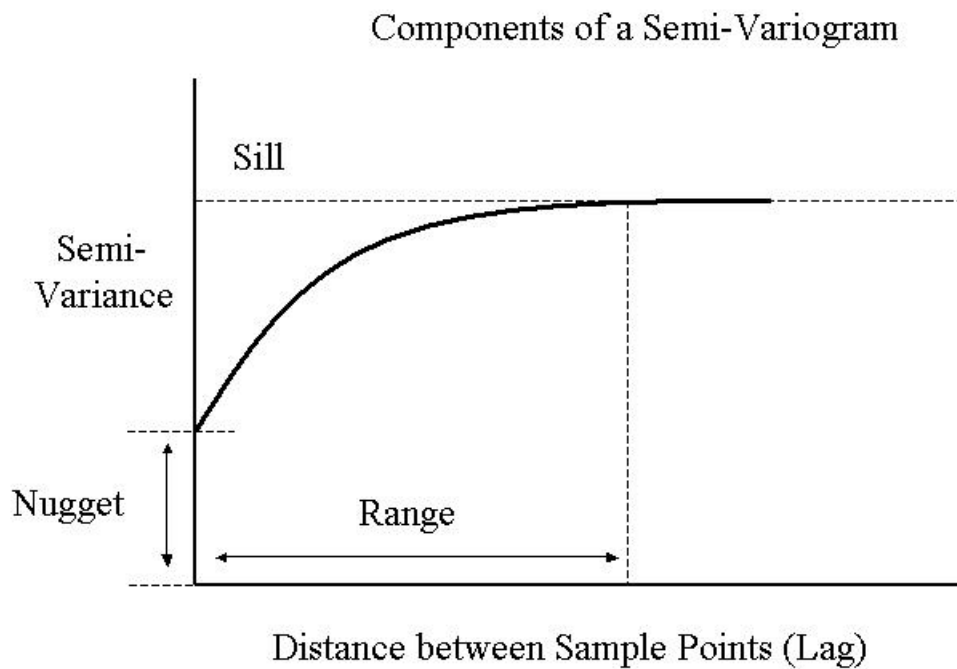
Figure 1. A diagram of the components of a spherical semi-variogram.

The most commonly used theoretical semi-variogram model in agricultural field studies is the spherical model. Mathematically, the standardized spherical model is defined as:

$$\gamma(h) = \{ \quad 1.5\,(h/a) - 0.5(h/a)^3 \, \} \qquad \text{if } h \leq a$$

$$\{ \quad 1 \qquad\qquad\qquad \} \qquad h > a$$

<div align="right">(Isaaks and Srivastava, 1989)</div>

The spherical model is considered a bounded or transitional model because it is characterized by an increasing level of variance, which will eventually reach a maximum value or sill. The rate at which the maximum variance is achieved distinguishes the spherical model from other categories of theoretical models.

Spherical models have been used to describe the spatial relationships present in a variety of soil and plant characteristics. Soil test results are commonly modeled using spherical semi-variograms (Soile et al 1999; Rover and Kaiser; 1999). In these studies, nitrogen, organic matter, and phosphorus were modeled using spherical

 models. Distributions of surface and sub-surface soil water contents have also been modeled extensively using spherical semi-variogram models (Western et al; 1999, Cahn et al. 1994, Wendroth et al. 1999). The range of spherical models used to fit the surface and sub-surface soil water data is quite large and is based primarily on the sampling density of the data. Spherical models have also been used to model the relationships found in yield data (Bhatti et al. 1991). There are numerous examples of studies that have used spherical models to describe the spatial distribution of field properties.

KRIGING

Once a spatial model is fit to the sample data, estimates of unsampled data can be determined using the kriging function. The kriging function uses the semi-variogram to weigh the impact of nearby sampled locations in the prediction of unsampled values. Field studies typically involve continuously changing variables that are sampled at discrete locations. Using kriging, unsampled locations can be interpolated and used to derive a spatial map of a particular variable. Kriging is a common process that is used to produce maps of variables such as yield data, nutrient concentrations, and soil moisture. These maps are useful for analyzing patterns and tendencies in a precision agriculture system.

Precision agriculture uses spatial information to classify management areas within a production field. One of the primary methods used to identify the different management areas of the field is the temporal persistence of patterns in a field (Sadler et al., 1998, Van Alphen and Stoorvogel, 2000). Typically, the most useful variables for identifying management zones are directly related to the crop yield. Soil test results, water distribution, and yield data are examples of datasets that can be used to determine the different management zones within a field. Yield datasets have been useful studied several times as a classifying variable (Lamb et al. 1997; Stevenson et al, 2001). Often, the variability of the yield between years is too high to make it an effective means of classification. Chemical and physical properties of the soil have also been used to define management zones. Unfortunately, the changes in the physical and chemical properties of the soil can occur in very short distances and have varying impacts on the production of a crop (Soile et al, 1999). Patterns used to

determine management zones at the field level need to account for small scale variations that will impact yield.

One potential way to explain the variability in yield data is to conduct controlled studies to investigate how the growing conditions around small areas of the plants affect the yield. The information gathered in these small areas could be used to explain variations that occur within larger areas of the field (Grayson et al. 1997). Soil moisture and nitrogen have been found to be two of the most important factors in determining the yields of corn. Soil moisture can vary dramatically within a field (Greminger et al, 1985; Famiglietti et al. 1998; Hupet and Vanclooster; 2002). A detailed study on soil moisture patterns could provide information to explain variability within yield data.

Scale, variability, and pattern persistence are elements that can affect the ability to recognize relationships that occur within datasets. Proper identification and evaluation is a key part in using this information to enhance understanding of the system. There are several mathematical tools available to analyze and evaluate the relationships that are present within datasets that include highly variable observations. Autoregressive Moving Average (ARMA) models are one of the tools used to study relationships among variables within complex and interdependent systems.

ARMA MODELS

ARMA models are common tools used to evaluate and forecast time/space series datasets. Time series datasets are observations of a single variable that are collected on a regular time interval such as daily, monthly, or yearly. ARMA models can also be used with one-dimensional, equally spaced spatial data such as transects.

For simplicity, the discussion of ARMA models will focus on analyzing time-based series; however, the assumption will be that a one-dimensional, space-based series could be substituted instead. An ARMA model is a two-part model consisting of an autoregressive model and a moving average model. An autoregressive model divides observations into a mean component, an autoregressive component, and an error value. The following equation is an example of an autoregressive model:

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots \phi_p A_{i-p} + \omega_I \qquad \text{(Nielsen and Wendroth; 2003)}$$

where ϕ and ω are the autoregressive parameters that are determined using linear regression when the mean value equals 0.

The moving average model differs from the autoregressive model in that the observation A_i is considered a linear combination of weighted random processes. In the following equation, a model of order q is used to describe observation A_i using weighted combinations of the random process $\omega_i, \omega_{i-1,}$

$$A_i = \omega_i - \beta_1 \omega_{i-1} - \beta_2 \omega_{i-2} - \ldots - \beta_q \omega_{i-q} \quad \text{(Nielsen and Wendroth; 2003)}$$

where $\beta_1, \beta_2, \ldots, \beta_q$ are the moving average coefficients.

A combined ARMA model can be written as:

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots \phi_p A_{i-p} + \omega_I - \beta_1 \omega_{i-1} - \beta_2 \omega_{i-2} - \ldots - \beta_q \omega_{i-q}$$

(Nielsen and Wendroth; 2003)

where $p + q + 2$ are unknown parameters

The work by Box and Jenkins (1976) has become the standard methodology for using ARMA models. Box and Jenkins used a three-step process to identify, evaluate, and forecast the ARMA model.

The identification step in ARMA modeling identifies the time series variable to be modeled, tests statistical characteristics of the observed variable, and identifies potential models to fit the data. The ARMA models have been designed to model time series datasets but not to explain the sources of variability (Nielsen and Wendroth; 2003). Most often, these models are used in cases where the sources of variability for the observed data have been previously established. The ARMA's initial tests are performed within the identification stage and are used to check the level of autocorrelation within the time series dataset, test the dataset's compliance with the guidelines for the ARMA model, and evaluate potential ARMA models. The tests performed within the identification stage are conducted based on the lag interval or the time interval between data points. The lag interval can be days, months, years etc; however, one of the requirements of the ARMA model is that knowledge of the relationship between the lag intervals and observations must be known. Another requirement of the ARMA model is that the variable to be modeled must exhibit stationarity.

Stationarity refers to a set of observations that has a constant temporal level of variation. Observations in a stationary time series dataset fluctuate around a mean value without the variance changing significantly over time. Datasets that do not exhibit stationarity must be made stationary before an ARMA analysis is performed. There are several methods that can be used to correct non-stationarity including

differencing of datasets or removing trends. Within the identification stage, stationarity tests are conducted on the time series dataset using the results from calculated autocorrelation functions.

The autocorrelation function, the partial autocorrelation function, and the inverse autocorrelation function are used to evaluate the time series dataset in the identification stage (SAS Institute Inc.,1993). These functions are used not only to test for stationarity but also to evaluate potential ARMA models. For each type of autocorrelation function, the results are plotted and are compared to theoretical correlation functions of different ARMA models. Using the theoretical ARMA models as a guide, the orders of the autoregressive and moving average portions of the model are defined.

The order of the autoregressive (AR) and moving average (MA) models are typically defined separately based on the variability of the time series dataset. In general, time series datasets are composed of combinations of random variations, that are considered to be stochastic variables, and repeating measurements, that are to be considered deterministic variables (Nielsen and Wendroth, 2003). The type of variation present in the time series dataset is the primary factor determining the order of the model. The order of the autoregressive model is significant in highly variable or stochastic datasets. The AR model is considered the "forward looking" portion of the model since it has the ability to forecast random variations in the system. As the order of the AR model increases, the changes in the pattern of the system's variability will tend to increase. In contrast, the moving average model is known as the "backward looking" portion because it forecasts using the trends of past observations

(SAS Institute Inc. 1993). Increasing the order of the MA model will tend to dampen the amount of variability found in the system. The order of the MA and AR models are determined using the variability in the system compared to the variability found in theoretical ARMA models. The identification stage of ARMA modeling is used to evaluate the observed time series dataset, check for stationarity, and define potential ARMA models.

The second stage of Box and Jenkin's ARMA modeling is the evaluation stage. In the evaluation stage, the potential ARMA models are tested, the autoregressive parameters are calculated, and the model is adjusted (SAS Institute Inc. 1993). During this stage, additional time series datasets can be added and removed from the model based on the model fit. Conditional least squares estimation and other statistical procedures are used to test the significance of each component of the model. Non-significant (> 0.05) portions of the model are removed and the conditional least squares test is repeated. Adding and removing AR orders, MA orders, and input datasets is normally performed several times to check the impact on model performance. This process continues until the model performs satisfactorily and only significant portions of the model remain.

The final stage of ARMA modeling is the forecasting stage. In this stage, the ARMA model can be used to predict current or future values of a dataset. In this stage, the estimated model is used to calculate data points and the errors associated with those data points. From the error calculation, a confidence interval can be determined for the forecasted data. The results of the forecasting section can be used to compare the impact of different input datasets, the autoregressive model, and the

difference between the model's predictions and observed data. The forecasting stage is the final stage of ARMA modeling that can be applied in many different ways to interpret various time series datasets.

ARMA models are typically used on time series and one-dimensional spatial datasets; however, with minor modifications, a 2-dimensional spatial dataset can be analyzed using an ARMA model. (Pegram and Clothier, 2001). ARMA models need to have a vector to define the start and finish of the dataset and the data needs to be equally spaced. A 2-dimensional dataset with x and y locations on a regular grid pattern does not have a defined start or finish but it does have points collected at a regular interval. The start/finish vector in a 2-dimensional dataset can be defined using a serpentine or circular pattern. Each xy location is given a unique number based on the serpentine/circular pattern; and that id variable is used to define a transect through the 2-dimensional spatial dataset. The resulting dataset with the id variable is equally spaced and has a defined start and end point. Although both of these patterns will produce a dataset that can be analyzed using an ARMA model, the serpentine pattern will maintain consistent spacing between rows of data points throughout the 2-dimensional plot. Additional testing of autocorrelations between rows can be performed with the serpentine pattern. As a result, the serpentine pattern is the preferred method to convert a 2-dimensional spatial dataset into a transect of equally spaced observations. Using a serpentine id variable, a 2-dimensional spatial dataset can be analyzed using an ARMA model.

For agricultural applications, several variations of autoregressive and moving average models have been used to analyze and forecast data. Single variable

AutoRegressive Integrated Moving Average (ARIMA) models, and multivariate State Space models are two of the more common types that have been used. Soil properties, such as temperature, texture, and soil moisture, have been modeled using the ARIMA and State Space methods.(Morkoc et al.,1985a; Morkoc et al.,1985b; Li et al. 2002) Yield data is another common agricultural variable that has been modeled using these time series techniques.(Stevenson et al.,2001; Boken, 2000) Several types of the autoregressive–moving average models have been used successfully to predict and analyze variables within agricultural studies.

OBJECTIVES

The objectives of this study were to investigate the temporal and spatial properties of surface soil moisture within small plots in a cornfield. A two-part study was conducted during the 2000 and 2002 growing seasons. The first part of the study focused on the temporal and spatial stability of the surface soil moisture in different production areas of the field. Soil moisture was sampled in high, medium, and low production areas to determine the spatial and temporal relationships that were present. It is hypothesized that spatial and temporal relationships will exist with different characteristics and stability based on the location in the field.

Based on the results of the first part, the second part of the study focused on autocorrelation relationships in the soil moisture data from each of the plots. The objectives for this part of the study were to evaluate the stability of the autocorrelation relationship found in the soil moisture data and how its predictive properties could be used to forecast soil moisture throughout the season. For this part of the study, it is hypothesized that the autocorrelation relationship will vary with the

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sampling period and as a result, the impact on predicting soil moisture will change over time.

MATERIALS AND METHODS - PHASE 1

This study was conducted utilizing plots located within a cornfield at the Beltsville Agricultural Research Center (BARC) in Beltsville, MD. The field is part of an ongoing precision agriculture study entitled the "Optimization of Product Inputs for Economic and Environmental Enhancement" (OPE3). The site is located on the eastern side of the BARC complex at 39°01'N 76°49'W. The OPE3 field consists of four 4-hectacre treatment sections (A,B,C,D) within a 25-hectacre field. Each section is used to study the environmental and economic impacts of different kinds of management practices. The data for this project was collected within Section A.

The soils in Section A were characterized by complexes of several soil series. In 1995, a detailed soil survey (1:12,000) of BARC completed by the USDA-Natural Resources Conservation Service (NRCS) identified three mapping units in section A. Downer-Muirkirk-Matawan Sandy Loam (DmB), Bourne Fine Sandy Loam (BuB), and Matawan-Hammonton Loamy Sand (MrB) were found in section A. Figure 2 illustrates the distribution of these soils within Section A. The soil report indicated that the expected yields of corn grown on the Downer complex (Dmb) and Bourne (Bub) soils would be 6.28 MT/ha while the Matawan complex (MrB) soil is slightly higher at 7.53 MT/ha. The NRCS report provided classification and production estimates for the soils in Section A.

Soil Mapping Units in Section A
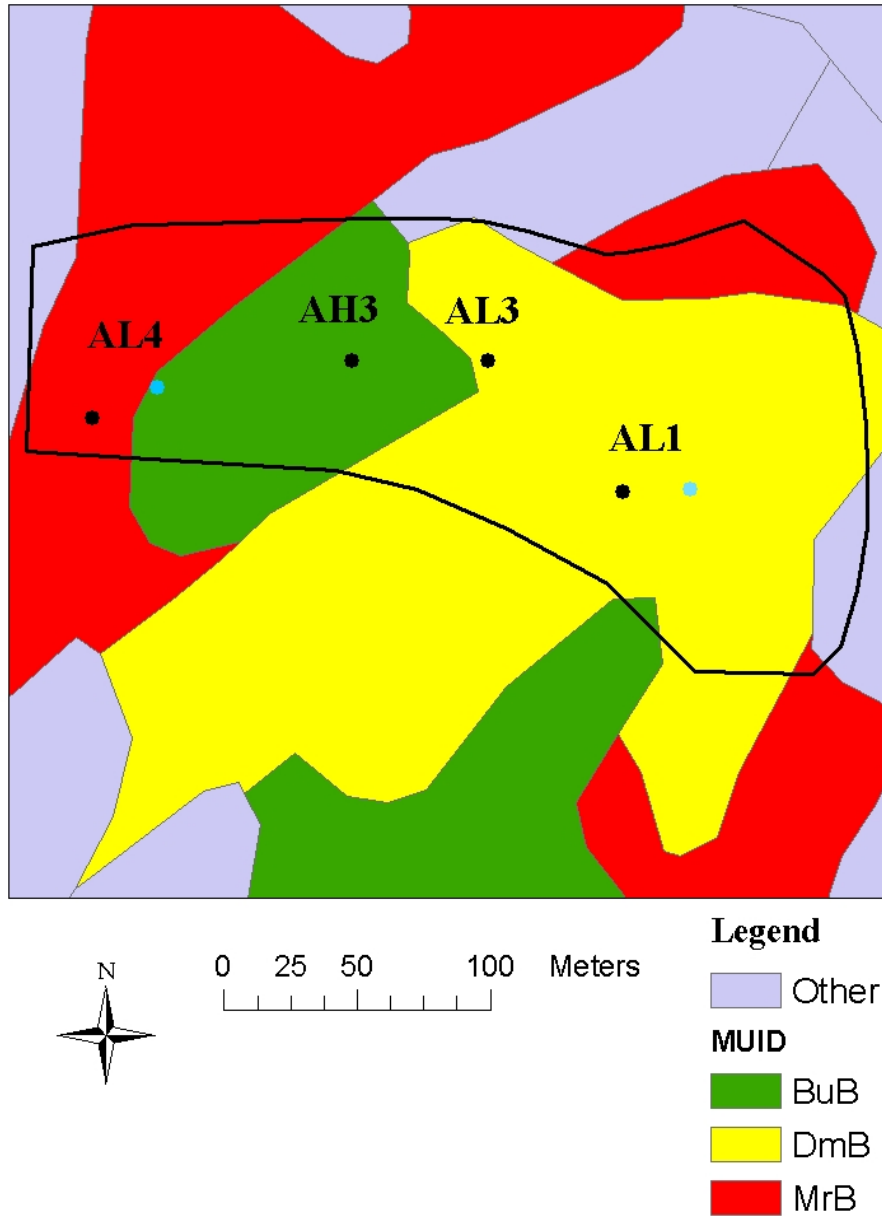
Figure 2. The soil mapping units present in Section A are Downer-Muirkirk-Matawan Sandy Loam (DmB, 2-5% slope), Matawan-Hammonton Loamy Sand (MrB, 5-10% slope), and Bourne Fine Sandy Loam (BuB, 2-5% slope). The black circles represent the centers of the 2000 surface soil moisture plots; the blue circles represent the centers of the 2002 plots.

A digital elevation map (DEM) of Section A was constructed from aerial photography to provide a detailed description of the topographic features. Within the section, there were approximately 1,500 defined elevation points that were determined using stereoscopic lenses and ground control points. Figure 3 illustrates the gradual change in elevation from east to west within Section A. Within Section A, the change in elevation is not dramatic and so, factors such as erosion and run off would be expected to have neglible impacts on our study. In addition to the detailed soil survey and elevation data, a historical record of the previous management activities in Section A was also available.

Within Section A, there were some areas identified as being less well suited to conduct this study. The eastern portion of the field was located near a wooded area that sheltered a large deer population. In previous years, significant deer grazing had negative impacts on the growth and development of the corn crop in this portion of the field. Without an effective method to control the grazing or to quantify its impact, areas in this section of the field were removed as potential study locations. Another area of concern was located in the center of Section A. At this location, a former access road had been plowed and turned into a production area. Although this portion of the field had been in production for several years, there were still concerns of reduced crop growth because of the previous roadbed in this portion of the field. For this study, the sample plots were positioned to avoid both of these areas.

According to the design of the OPE3 project, the management practice to be studied in Section A was a single-rate system. In a single-rate system, management decisions for fertilization, seeding, and pesticide application rates are determined and

Elevation in Section A

Legend (Meters)

35.6 - 36.0	38.0 - 39.0	41.0 - 42.0
36.0 - 37.0	39.0 - 40.0	42.0 - 43.0
37.0 - 38.0	40.0 - 41.0	43.0 - 44.0
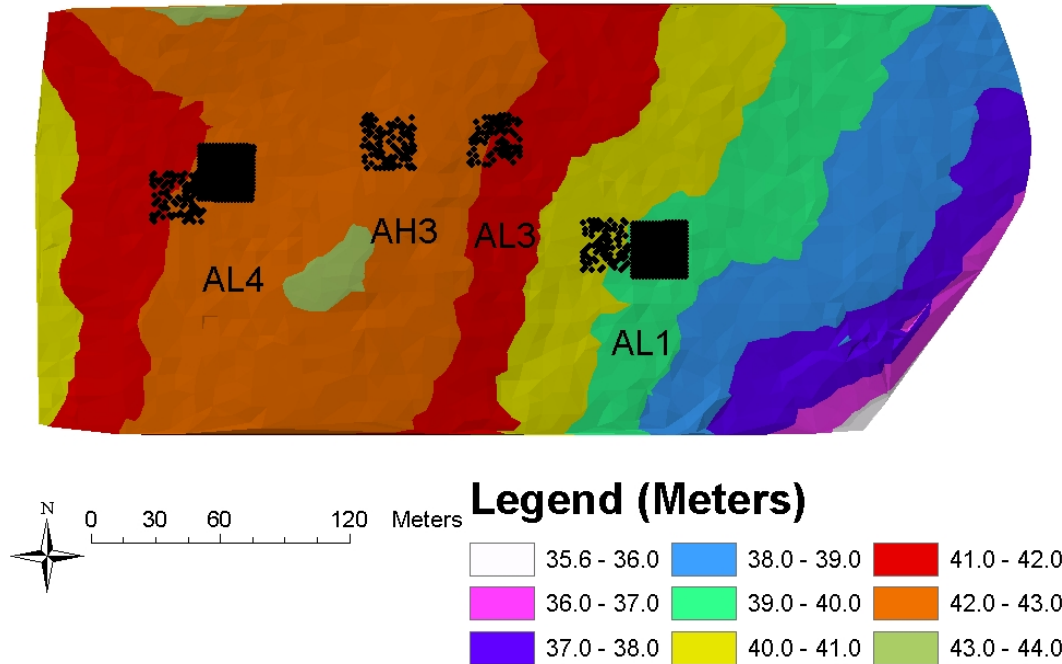
Figure 3. A representation of the change in elevation found within section A of the OPE3 field. The black squares represent the surface soil moisture plots sampled in the 2000 and 2002 growing season.

applied evenly to the entire field area. In mid-May, soil samples (0-30cm) were taken from several areas to determine the average nutrient status of the soil. The samples were sent to the University of Maryland Soil Testing Lab where the samples were analyzed for pH, magnesium, potassium, phosphorus, calcium, nitrates, and texture. In late May of 2000, the soil was prepared using a tandem disk harrow set to 15.24 cm deep. On June 2, 2000, a digested liquid dairy manure was applied to Section A of the field at a rate of 93,500 L/ha. The dairy manure was analyzed and found to contain 7.60 kg N and 3.375 kg P_2O_5 per 3,790 liters. The manure was incorporated

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into the soil on the same day using the tandem disk harrow. Eight days after the manure application and just before planting, a Krause Landsman soil finisher set at 15.24 cm was utilized on the field. Corn (*Zea mays* L; Pioneer 33A14) was planted in 76-cm rows on June 10th. Five days after planting, two herbicides were applied to control weed growth using a surface broadcast spray. Bicep II Magnum (atrazine and metolachlor) was applied at 3.04 L/ha and Dual II Magnum (metolachlor) was applied at 0.701 L/ha. After emergence, 15 soil samples (0-30cm) were taken from Section A on a 50 m grid pattern to determine the Pre-Sidedress Nitrogen Treatment (PSNT) values and the soil moisture content. Based on the average PSNT value, the sidedress nitrogen treatment was adjusted. According to the Maryland Soil Testing lab, the desired nitrogen fertilization rate for corn in this area was 112 kg/ha. The side dress application rate was adjusted by the PSNT values to achieve this rate. On July 13, a nitrogen side dressing was injected into the soil at 50.4 kg/ha and additional herbicides (Bicep II Magnum and Dual II Magnum) were spot-applied to areas that continued to have significant weed problems. On November 11th, Section A was harvested using a combine and the yield was recorded using a yield monitor. From 1999 to 2003, the yield data for OPE3 was collected using a combine mounted Agleader 2000 yield monitor system, which determined the amount of grain harvested as well as the combine's geographical location within the field. The yield monitor was set to output data on the grain yield and location every second as the combine moved through the field. In 2000, the single rate management of Section A was conducted according to the experimental design for the OPE3 project.

Weather conditions in 2000 at OPE3 were monitored and recorded using a Campbell weather station (Campbell Scientific, Inc. Logan, UT) that was located at the BARC dairy approximately 1 km to the west. The dairy weather station has a Campbell CR10x datalogger, which was programmed to continuously monitor the weather sensors, average the data every 15 minutes, and output the values to a text file. On the weather station, there were sensors to measure the temperature and humidity (12-gill Vaisala HMP35C), wind speed and direction (RM Young 05103 Wind Monitor), solar radiation (Licor LI200X silicon pyranometer), and rainfall (TE525 Tipping Bucket Rain Gage). Each sensor, except the rainfall gauge, was mounted on a 3 m tower; the rainfall gauge was mounted 1 m off the ground on a pole 3 m from the main tower. The weather station data monitored continuously for the 2000 growing season.

For this study, two types of soil moisture data were collected. The first set of data focused on the distribution of the subsurface water contents and was a permanent part of the OPE3 study. A network of probes was located throughout the field and was continuously monitored using dataloggers. This dataset provided detailed temporal measurements of the soil profile at single points. The second dataset focused solely on the surface soil moisture. This dataset was a pattern of measurements conducted multiple times during the growing season. The surface soil moisture measurements were designed to provide detailed spatial and temporal information over small areas. The design of the study was to use both types of measurements to characterize the distribution of soil moisture.

Subsurface water contents in section A were monitored using 12 permanently installed Sentek EnviroSCAN soil moisture capacitance probes (Sentek Sensor Technologies; www.sentek.com.au) that were part of the long term OPE3 study. The EnviroSCAN probes can be configured to sample soil moisture between 10 cm and 200 cm at intervals of 10 cm. In Section A, the EnvironSCAN probes were configured to provide 3 sampling densities based on the soil's infiltration rate. In areas of the field where the infiltration rate was high, the "L" configuration was used to sample soil moisture at depths of 10, 30, 50, 80, 120, 150, and 180 cm. In areas of medium infiltration rates, the "M" configuration was used to sample soil moisture at depths of 10, 30, 50, 120, 150, and 180 cm. In areas with low infiltration, the "H" configuration was used to sample soil moisture at depths of 10, 30, and 80 cm. There were 4 probes of each configuration located in Section A. The probes were connected to a Sentek Enviro-Scan system, which was set to collect soil moisture data every 10 minutes. Starr et al (1998) have discussed the use and sensitivity of these probes to monitor soil moisture levels under a cornfield. Due to the frequency and profile coverage of these probes, it was considered beneficial to the study to establish surface soil moisture sampling plots in close proximity to the Sentek probes.

Surface soil moisture measurements were acquired using two capacitance probes (Delta-T ML1 Theta) and two Campbell CR-10 dataloggers. The capacitance probes provided flexibility and accuracy for the surface soil moisture measurements that was not available using other methods such as neutron scattering (Mohamed et al. 1997). The measurements were made by inserting the probe into the surface soil and using the datalogger to record the data. The sampling depth of the Theta probe is 0-5

cm and the diameter of the sample is approximately 3 cm.   The Campbell dataloggers were used to control and store the data from each probe.   Measurements were acquired in the early afternoon (12 pm – 2 pm) in order to allow the plant canopy and soil surface some time to dry from any dew or condensation from the previous night. Plots were setup in the field and marked using PVC flags. Repetitive sampling of the plots was conducted throughout the season and the sampling order varied between sampling dates. In each plot, the total sampling time of the plot was less than one hour. At the completion of each sampling period, the data were downloaded from the dataloggers to a PC for editing and analysis. A summary of the surface soil moisture sampling dates for each plot in 2000 can be found in Table 1.

The 1999 corn yields were a factor used to determine the locations for the surface soil moisture plots.   Within Section A alone, the yield dataset resulted in several hundred measurements each year. In order to determine differences in yield throughout the field, the raw yield data were grouped into areas and the production values were compared. For 1999, 60 25-m by 25-m blocks were used to aggregate the observed yield throughout Section A. The aggregated areas were defined as low, medium, and high producing areas based on the following yield ranges: high = 4.707 – 7.846 MT/ha, medium = 1.569 - 6.277 MT/ha, low = 1.569 - 4.707 MT/ha.   The location of the surface soil moisture plots were selected to represent land areas with a range of production values.

Plots for surface soil moisture samples were established at four locations in Section A.   Each area contained a Sentek soil moisture probe and represented a

Table 1.   Sampling dates of 2000 surface soil moisture sampling with ML1 Theta probe.

Date	AL1	AL3	AH3	AL4
171	X	X		
172			X	X
178	X		X	
188		X		X
192	X	X	X	
193	X			X
195		X		
196			X	
197	X		X	
200	X	X		X
203		X		X
217	X	X	X	X
222	X	X	X	X
230	X		X	
235	X			
236			X	X
251	X	X	X	
Totals = 17 sampling days	11	9	10	8

different level of yield production. Each plot was labeled using the block coordinates of the Sentek probe that was located closest to the plot. (AL1, AL3, AL4, or AH3) Figure 4 is a map illustrating the location of the 4 plots in section A and their proximity to the soil moisture probes. AL4 represented one of the lowest producing areas of the field while AL1 represented one of the highest.   AH3 and AL3 represented yield quantities in the middle. Once the plot locations were identified, a procedure was used to systematically determine the locations of the detailed soil

OPE3 Section A - Soil Moisture Sampling Layout

Location of
NASA Sensor

AH3

AL3

AL4

AL1

Legend

⚑ Sentek Probes

▲ 2000 plots

• 2002 plots

0   25   50   100   Meters
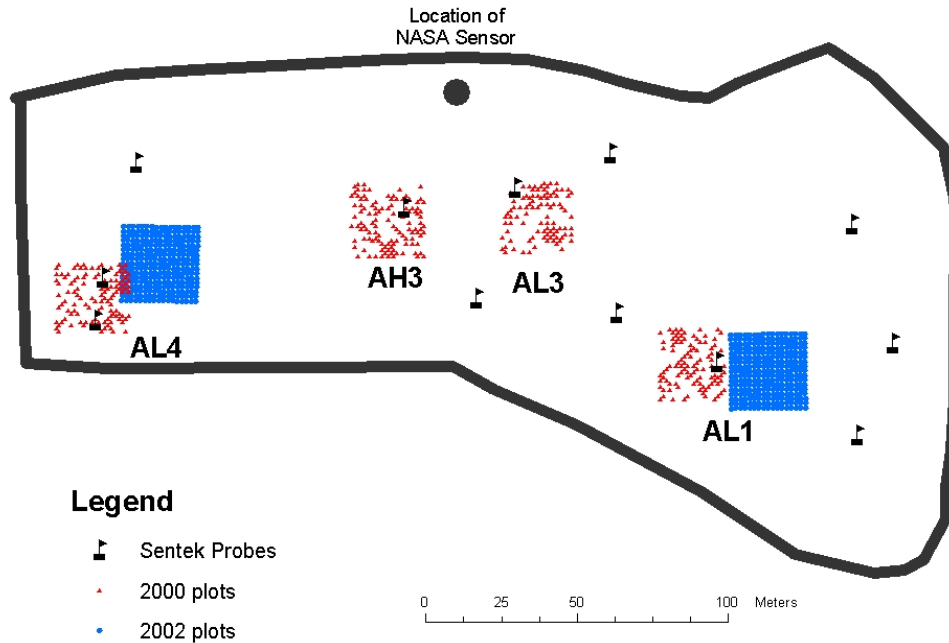
Figure 4. The layout of plots in Section A of OPE3 site. The red points illustrate the areas sampled for soil moisture during the 2000 growing season plots. The blue squares represent the plots sampled for soil moisture in 2002. The flags represent the locations of the permanently installed Sentek soil moisture probes.

moisture sampling points so that each plot could be sampled in a similar fashion, with good spatial coverage, and in a timely manner.

The method used to determine the surface soil moisture sampling locations was a slightly modified version of a sampling design published by Russo (1984) and was designed to produce an optimized set of sampling points to calculate the sample semi-variogram. In Russo's design, the locations of sampling points were determined by using a combination of systematic and random spacing. Based on the number of pairs per lag distance, the method adjusted the positioning of some of the locations in

order to balance the number of pairs per lag distance. For this study, the surface soil moisture sampling points were selected using a systematic and random process. In order to ensure relatively stable soil moisture conditions throughout the sampling interval, the sample time was limited to 60 minutes. From previous experience with the soil moisture probes, 120 locations could be sampled within 60 minutes. Overall, the goal of the process was to select 120 surface soil moisture measurement locations within the 25 m by 25 m plot.

The first step in selecting the sampling locations was to construct an offset 2m grid arranged in 25 rows and 25 columns over the entire plot (Figure 5). The offset grid established 312 potential sampling locations within each plot. From these 312 points, a subset of 120 points would be selected as the soil moisture sampling points. Before the points were selected, a blocking procedure was used to break the plot into smaller regions.

The goal of the blocking procedure was to subdivide the plot so that the surface soil moisture measurements would be distributed throughout the area. Each plot was broken into twenty-five 5 by 5-m blocks. Each of the blocks contained 12 or 13 points from the original 312 points. Instead of sampling each of the 25 blocks at the same rate, a variable rate system was used to produce an even distribution of distances between pairs of points. Three sampling rates, low (2 or 3 points), medium (5 or 6 points), or high (12 or 13 points) were applied to the blocks. Within each block, the actual sampling locations were randomly chosen from the 12 or 13 points. The result of the blocking procedure was a distributed set of sampling locations that had varying measurement densities.

Method for Determining Surface Soil Moisture Sampling Locations

Block Sampling Density	Number of Measurements (Theta Probe)	Block Assignments Per Plot
High	13	1
Medium	6	10
Low	3	14
Total	115 Points Per Plot	25 Blocks per Plot
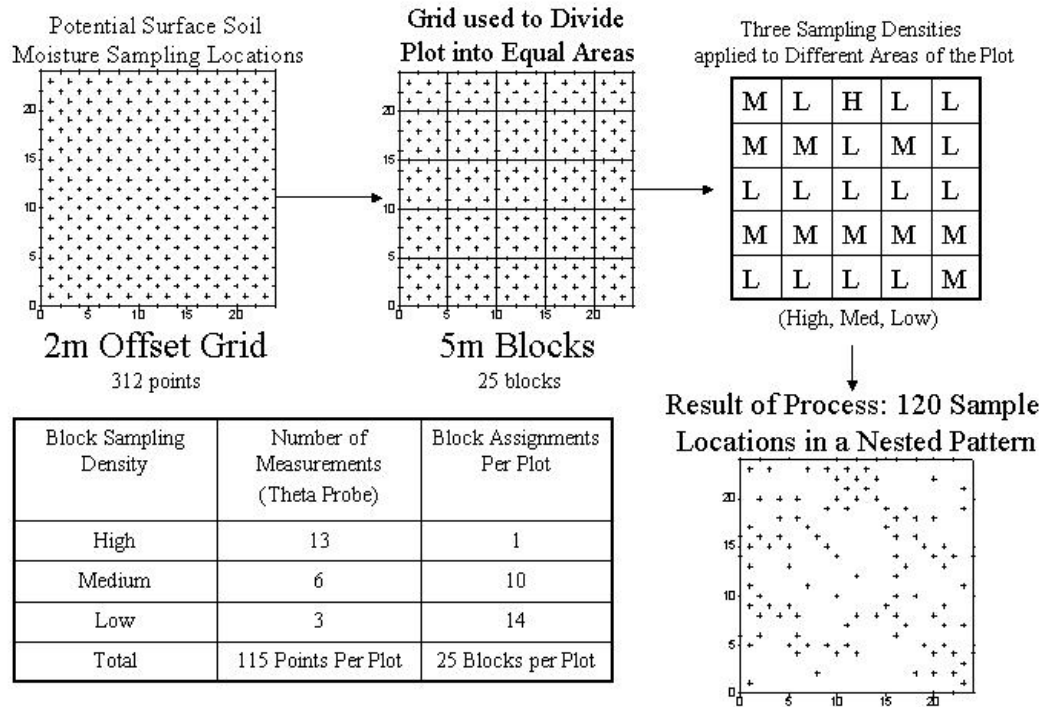
Figure 5. An illustration of the method used to determine the surface soil moisture sample locations for the 2000 growing season.

Each plot contained the same distribution of sampling densities, which resulted in a total of 120 sampling locations. The sampling densities in each of the plots were 14 blocks of low sampling density, 10 blocks of medium density, and 1 block of high density. Once the locations were determined, global positioning system coordinates were used to establish the actual locations within the field. At each location, a PVC flag was used to mark the sampling area within the field. These locations were sampled for surface soil moisture throughout the growing season.

MATERIALS AND METHODS - PHASE 2

The management practices in Section A for the 2002 growing season were identical to the practices used in the 2000 growing season except for slight variations

in the timing of the procedures. The initial tillage on the field was performed in early April using the tandem disk harrow set to a depth of 15.24 cm. On April 12, 2002, liquid processed dairy manure was applied at a rate of 93,500 L/ha to section A. The manure had been tested by the University of Maryland and was found to contain 8.01 kg of N and 3.83 kg of P_2O_5 per 3,790 gallons.   On the following day, the manure was incorporated into the soil using the tandem disk harrow. Prior to planting, a Krause Landsman soil finisher set at 15.24 cm was utilized on the field. Corn (*Zea mays* L; Pioneer 33A14) was planted in 0.76 m rows on April 19th-20th. Following planting on April 24th, Bicep II Magnum (atrazine and metolachlor) was applied at 3.04 L/ha and Dual II Magnum (metolachlor) was applied at 0.701 L/ha to control weed growth using a surface broadcast spray. On May 28th and 30th, 15 soil samples (0-30 cm) were taken on a 50 m grid to determine the PSNT values. On June 16th, a nitrogen side dressing was applied at 39.2 kg/ha and sporadic application of pesticides (Bicep II Magnum and Dual II Magnum) to weeds was performed. Section A was harvested on Oct 2nd, 2002. The management process in this section of the field was consistent with the practices in the 2000 growing season.

In 2002, a Campbell weather station was erected within Section B of the OPE3 field to monitor the growing conditions. The Section B weather station had an output interval and a set of sensors that was similar to the dairy station; however, it was located much closer to Section A. The Section B weather station was equipped with a HMP45C temperature and relative humidity probe and a TE525 Tipping bucket rain gauge. There were additional sensors on this weather station to monitor wind speed/direction, light levels, and CO2 concentration; however, that information

was not used in the scope of this study. In 2002, the weather data from the Section B station was used to monitor the growing conditions near the field.

The surface soil moisture sampling in 2002 was conducted in two 25 by 25-m plots. The 2002 plots were located in close proximity to the AL1 and AL4 locations in 2000. These plots were designated AL102 and AL402 to differentiate them from the 2000 sampling locations. In 2002, several changes were made to the surface soil moisture sampling based on concerns from the 2000 dataset and to address the specific data needs of the second part of the study. One concern from the 2000 data was the impact of the row/inter-row sampling position since the surface soil moisture dataset was collected using samples taken from row locations and interrow locations. Van Wesenbeeck et al. (1988) found there to be variations in soil moisture depending on the row or interrow sampling position. In 2002, all of the sampling points were positioned within the row to minimize the effect that row position had on the data. Another concern from 2000 was the impact that the unbalanced sample strategy had on the directional component of the semi-variogram. In 2002, an even distribution of points was arranged into 17 rows and 17 columns with sample points located every 1.54 m. There were a total of 289 sample locations per plot. The final dataset was comprised of a complete set of equally spaced measurements that could be used for ARMA forecasting. The overall size of the plots remained about the same (25 by 25-m) but the number of samples per plot was increased from 120 to 289.   The modification to the sampling of the plots for 2002 was expected to have a beneficial impact on the goals of this phase of the study.

Another change that was made in 2002 was a reduction in the number of plots. A change in the total number of plots was based on the sampling time and the presence of a NASA study nearby. With the increased sampling, the time required to sample the plots almost doubled. In addition to timing concerns, NASA was performing a study in the northern section of Section A. The NASA study involved soil surface scans of the field and as a result, pedestrian traffic was discouraged within ~100 m of their instrumentation. (Figure 4). Since the center two plots of the 2000 study fell within the NASA study and there were concerns involving sampling times, a decision was made to remove the two plots from the study.

The soil moisture measurements were designed to acquire a detailed spatial and temporal description of the surface and sub-surface water contents for the plots throughout the growing seasons. The surface moisture measurements were to have provided the bulk of the desired spatial and temporal information. These measurements were designed to provide information similar to data acquired from remote sensing applications but with a higher level of spatial resolution than is currently available for moisture data. The sub-surface measurements would have been used to supplement the surface data and provide detailed temporal measurements of the below ground soil moisture changes at specific points. Unfortunately, the sub-surface data from the Sentek probes was mostly unavailable. In 2000, a lightning strike damaged the Sentek system in Section A and repairs were not completed until after the conclusion of the 2000 growing season. In 2002, there were some significant outages in the Sentek data for the AL4 plot while the AL1 plot had an almost complete dataset. Without complete datasets for the sub-surface water

contents, the soil moisture analysis focused primarily on the surface soil moisture plots.

After the 2000 growing season, a new Delta-T ML2 Theta capacitance probe and HH2 datalogger (Delta-T Devices Ltd; Cambridge, England; www.delta-t.co.uk) were acquired. The ML2 probe is very similar to the ML1 probe with only minor modifications to the sensor. The ML2 probe was supposed to be less sensitive to the salt content of the soil than the ML1 probe (Miller and Gakin). Since the soils in the study did not have a high salt content, the improvements to the ML2 probe should not have affected the probe's response to the soil moisture. A laboratory calibration of both probes was conducted to verify this theory.

The calibration of the Theta probes was performed utilizing soil columns to test the factory calibration curves and the differences between the ML1 and ML2 probes. Surface soil (0-5 cm) from 4 locations in each of the 2002 field plots was collected on October 18, 2002. For each plot, the 4 locations were combined in a bucket and oven dried at 70 degrees C for 5 days. Soil columns were constructed by mixing 200 grams of the oven dried soil with different volumes of water (25 ,50 ,62 ml) and packing the soil/water mixture into six 7.5 cm (H) by 5 cm (W) sections of PVC pipe. For each soil/water combination, the cores were sampled three times by each probe. Each core was then dried and weighed again. A relationship between the volumetric water content and the millivolt signal was derived (Figure 6). The figure shows that the sensors have similar responses to changes in water content and the factory calibration curves were very close to the observed calibration curves.

Calibration Curves For Theta Probes

ML1 equation
y = 0.0451x - 0.2644
R^2 = 0.9603

ML2 equation
y = 0.0445x - 1.5085
R^2 = 0.9821
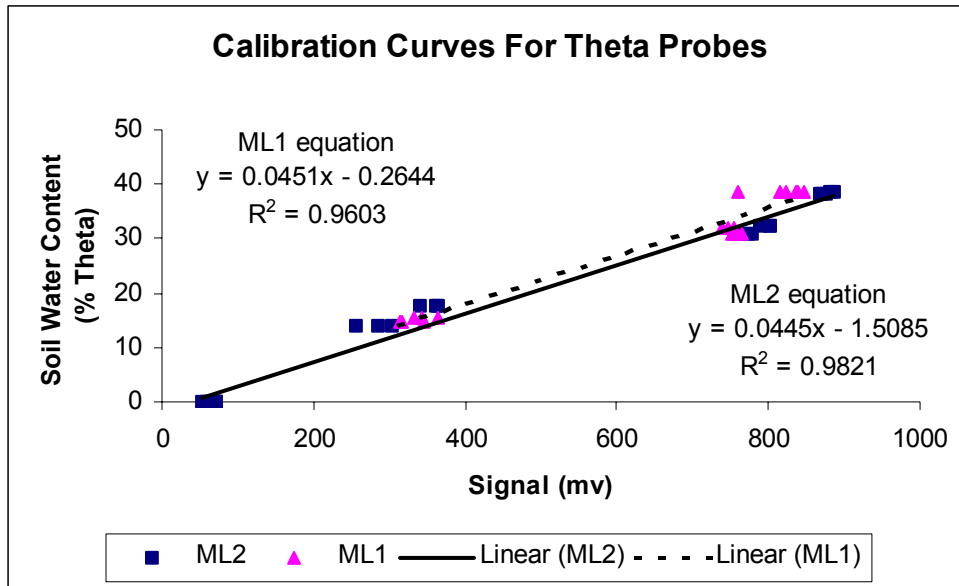
Figure 6.   Responses of Theta ML1 and ML2 capacitance probes to different combinations of soil/water mixtures prepared in the lab and packed into poly- vinyl chloride (PVC) columns. The solid lines represent linear regression lines for each sensor.

Mean relative differences of the surface soil moisture were calculated to examine the temporal stability of the measurements. The mean relative difference of the surface soil moisture is defined as (Vachaud et al.,1985):

$$\delta_{ij} = (\theta_{ij} - \theta_j)/\theta_j$$

where θ_j = the mean water of the field at time j and θ_{ij} is the water content at location i at time j.

The mean relative difference removes the average water content each measurement time so that the variations of measurements around the mean can be compared throughout the season. Typically, the mean relative difference values are ordered from lowest to highest and presented with error bars to describe the variability found at specific sampling locations. The mean relative differences of the surface soil

moisture data is used to evaluate the stability of individual locations as compared to the average conditions present within the field.

GEOSTATISTICAL ANALYSIS

Sample semi-variograms were calculated for the surface soil moisture data in 2000 and 2002. For the 2000 datasets, the semi-variograms were calculated using 25 separate lag distances each separated by 0.4 m. The maximum lag distance for the plots was 11 m. The number of pairs per lag were relatively balanced and averaged out to approximately 200 pairs; the minimum number of pairs did not fall below 90 pairs. For the 2002 surface moisture measurements, the plot size was smaller and the measurement rate was higher. As a result, the semi-variogram was calculated using the same number of lags (25) but a smaller lag distance (0.3 m) and a shorter range (7.5 m). The number of pairs in the 2002 measurements averaged out to approximately 500 pairs per lag distance. In both cases, the Surfer software package (version 8; Golden Software, Inc) was used to calculate the sample semi-variograms. The sample semi-variograms were initially calculated without a directional component.

In a few situations, the results of the semi-variogram calculations did not reach a definitive sill value; in these cases, directional variograms were calculated. The directional semi-variograms were calculated using a 30 degree search window that was oriented at 0, 30,60, and 90 where 0 was east/west and 90 was north/south. For both years of soil moisture data, the semi-variograms were calculated separately for each sampling date of each plot. Once the sample semi-variogram had been

calculated a theoretical semi-variogram model was fit to each day to see if the spatial structure of the soil moisture measurements changed over time.

Once the sample variogram had been calculated, a theoretical semi-variogram model was used to fit the data. For each day, a spherical model was used to fit the data. Hohn (1988) has documented problems using automated procedures to find the best fitting theoretical models for sample semi-variograms in cases where the sample semi-variograms have small numbers of points. As an alternative, he has suggested that a visual fit can be justified. The software system had options to do either an automated fit or a visual fit. The results of the automated procedure did not fit the model very well; so visual fitting was performed to model the sample semi-variogram. Some general guidelines were followed during the visual fitting process. The nugget values were kept as constant as possible. The random variation contained in the nugget throughout the season was thought to have been relatively constant. The range and sill settings were varied based on the data for each day. In the fitting process, the preferred theoretical model was a non-directional spherical model; however, in cases where the sample semi-variogram did not achieve a definitive sill, an anisotropoic model was used to model the variance. The results of the fittings were plotted and the nugget, sill, and range values were recorded. The Surfer software package (version 8; Golden Software, Inc) was used to fit the theoretical semi-variogram models to the sample semi-variograms. The geostatistical analysis was performed to determine the spatial relationships present within the surface soil moisture measurements and how those relationships changed over time and space.

Sample semi-variograms and theoretical semi-variograms were used to determine the spatial relationships for the yield data in Section A for the 2000 and 2002 growing seasons. The sample semi-variograms were calculated using all of the yield monitor data from Section A. The sample semi-variograms were calculated using the Surfer software package (version 8; Golden Software, Inc). For the 2000 yield data, the sample semi-variograms were calculated using 25 lags with a lag distance of 3 m for a maximum lag distance of 75 m. In 2002, the scale of the yield sampling changed slightly in response to combine speed so the lag distance was increased to 4 m. The 2002 calculations were conducted for 25 lags and a maximum lag distance of 100 m. For both years, omni-directional semi-variograms were calculated. Once the sample semi-variogram was determined, a visual fit of a theoretical model was performed. From the visual fit, the sill, nugget, and range of the data were determined. Of the three characteristics, the range value was considered the most important because of its potential impacts on the spatial relationships in the surface water content data. The geostatistical analysis of the yield data was used as background information in the spatial analysis of the surface soil moisture data.

FORCASTING ANALYSIS

Soil moisture data can be very labor intensive and expensive to acquire; so the last part of the study was spent evaluating the forecasting potential of the 2002 surface soil moisture datasets. The goal was to forecast the water content measurements in the later parts of the season using a combination of an autoregressive function and datasets from an earlier sampling date. The forecasts

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would be used to test the ability to predict the surface soil moisture within each plot under different conditions. The first step was to add a serpentine variable to surface soil moisture measurements to convert the 2-dimensional spatial dataset to an equally spaced transect dataset.

The serpentine pattern was constructed by adding an id variable to the surface soil moisture data starting in the southwest corner of each plot. The pattern had 17 points in each row and resulted in 289 equally spaced sampling intervals. Once the id variable was created, the first step in the autoregressive modeling was used to identify and evaluate the dataset.

The first step of the autoregressive modeling was to identify the autoregressive model. The modeled data was tested to 34 lags so that measurements in the neighboring row would be tested. The autocorrelations, cross correlations, partial autocorrelations, and inverse autocorrelations were calculated to determine whether the data exhibited stationary. In the evaluation stage of the ARMA modeling, the autoregressive model was defined, the input variables were defined, and each factor was tested for significance.

The first stage of the evaluation procedure was to define the ARMA parameters. Due to the variability in the data, the moving average (q) parameter was set to 0 so that only an autoregressive model would be used. As a starting point, the autoregressive order parameter (p) was set to 34 to evaluate the observations that occurred directly before the current observation as well as the observed values that had occurred in the adjacent row. The significance of each order of the autoregressive parameter was checked using a conditional least squares estimation

procedure. Each sampling date was tested separately. Results from the conditional least squares estimations found that the autoregressive parameters were significant at a level of 3 or less for all of the sampling dates. Once the autoregressive parameter (p) was tested, the input datasets were the next step in the evaluation procedure.

Once the autoregressive parameter was defined, additional testing was performed to evaluate the information from some of the previously sampled datasets. In this test, each of the previous datasets was evaluated using conditional least squares estimations to determine whether it was adequately significant to be included in the model of the current dataset. The initial model of the current soil moisture data included all of the previously sampled datasets and the autoregressive parameter. Using that model, a conditional least squares test was performed and each element of the model was tested for significance. Non-significant (>0.05) portions of the model were removed and the conditional least squares test was repeated. This process continued until only significant portions of the model remained. The final model, which included the autoregressive parameters and the significant input dates, was used to perform a forecast of the current dataset.

Once the identification and evaluation stages were completed, forecasts of the surface soil moisture data were performed. The initial forecasts were conducted using the complete model, which included all orders of the autoregressive parameters and all of the significant input datasets. For each day, the AR coefficients were calculated and recorded for each of the model components. The results of the forecasts were plotted against the observed data and R-squared values were calculated. Once the complete model had been evaluated, each of the input datasets

and autoregressive parameters were removed one by one to determine the amount of influence each one had on the forecasted data. The changes to the forecasts were used to evaluate the effectiveness of the input datasets and the autoregressive parameters in the forecasting of the surface soil moisture.

RESULTS AND DISCUSSION

PRECIPITATION - 2000

The precipitation observed in Beltsville during June, July, and August of 2000 exceeded the 30-year average rainfall during that time period. The observed rainfall for June, July, and August was 11.8 cm, 14.9 cm, and 10.9 cm, respectively. The average Beltsville precipitation from 1971-2000 was 9.11 cm in June, 10.39 cm in July, and 9.37 cm in August (Maryland's State Climatologist's office). During the 2000 growing season, there was a large number and an even distribution of rainfall events (Figure 7). The intensity of the rainstorms was mild to moderate; and so, there were not significant problems with flooding, runoff, or erosion. In the 2000 growing season, the amount and distribution of rainfall lead to above average soil moisture conditions.

SURFACE SOIL MOISTURE - 2000

The temporal range of the mean surface soil moisture data for the plots during the 2000 growing season was 10-30% volumetric water content (Figure 8). In general, slightly higher plot mean soil moisture values (3-6% higher) were found in AL1 and AL3 plots compared to the AL4 and AH3 plots. Over the duration of the
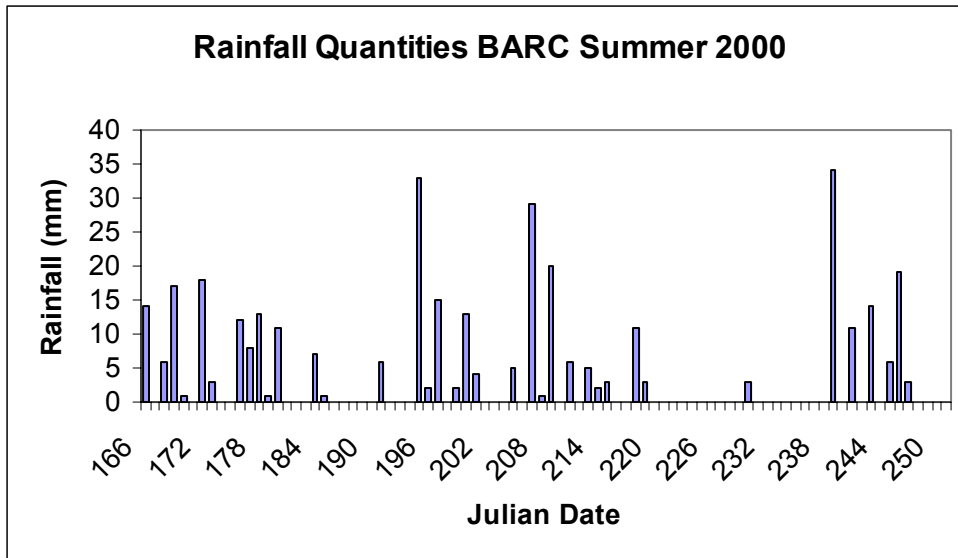
Figure 7. Daily rainfall quantities in millimeters recorded in Beltsville, MD during the 2000 growing season. The 2000 data was collected from the Beltsville Agricultural Research Center's Dairy weather station.

growing season, the soil moisture levels remained high and there were only four rain-free intervals that exceeded 4 days. The intervals without rain were July 3rd – July 11th (Days 186-194), Aug 6th – Aug 15th (Days 220-229), and Aug 18th – Aug 24th (Days 231-238). All the surface soil moisture sampling dates in the 2000 growing season were within 4 days of a rain event, so, the data is representative of the wetter portion of the potential range of water contents. The standard deviations of the average plot soil moisture varied only slightly over time during the growing season. Rainfall events or dry conditions (ie. extreme values) resulted in relatively uniform soil moisture conditions, and hence, smaller standard deviations. Intermediate conditions had large ranges of soil moisture values, which tended to have higher standard deviations. The temporal variations of the spatial plot water contents were directly related to the rainfall events during the growing season.
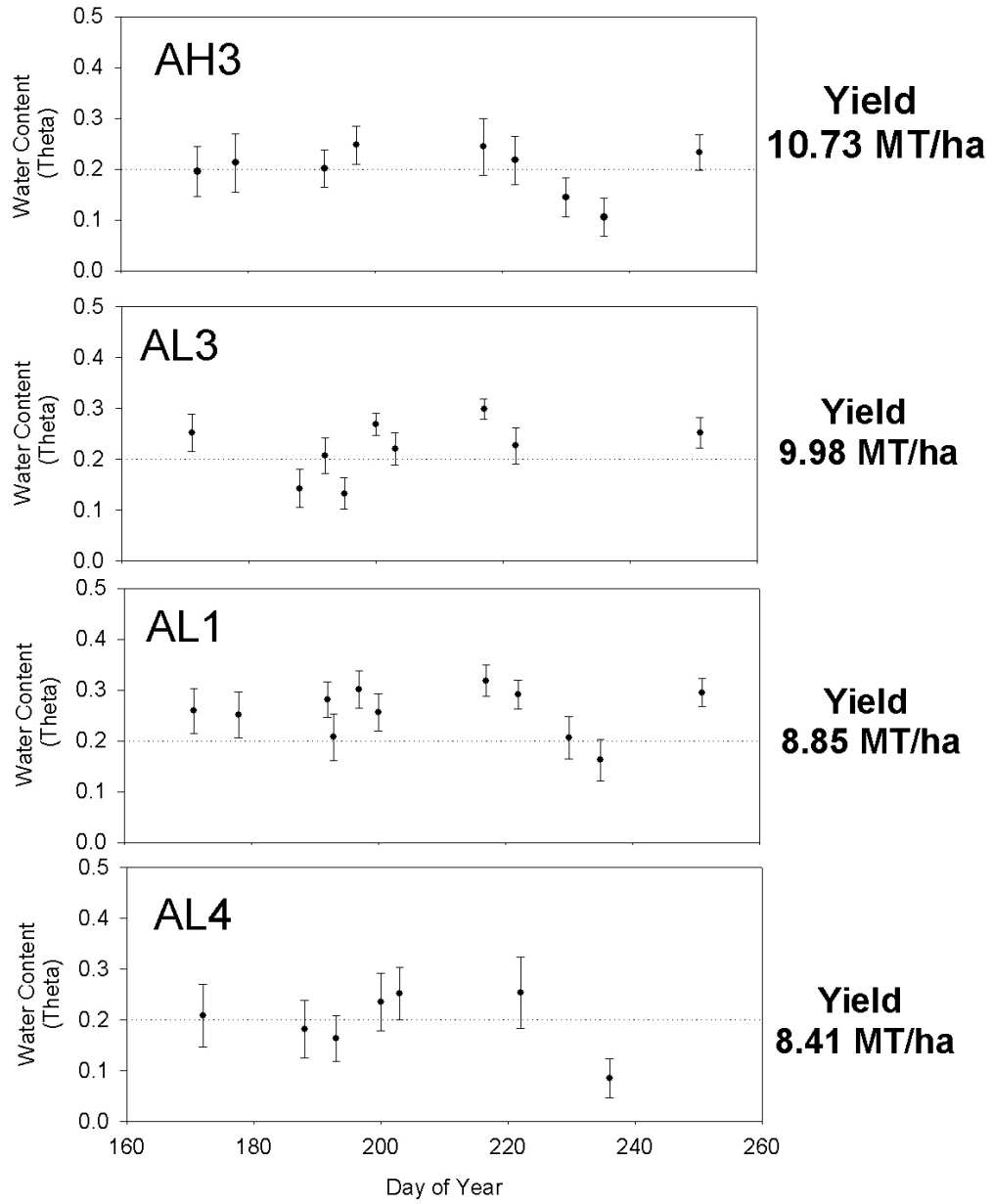
Figure 8. The mean and standard deviation of the surface soil moisture in each of the 2000 plots throughout the season.

Contour plots of the seasonal averages and variances of the observed surface soil moisture were constructed from the 2000 datasets (Figure 9). The nested design used for the soil moisture sampling resulted in an uneven distribution of points, which potentially contributes to smoothing of the data during the kriging procedure. The sampling locations are illustrated in the first column of Figure 9 to clarify the locations of the sampled data. In general, the distribution of the sampling points does not appear to have dramatically influenced the soil moisture contour plots because the positions of the contours appears to be mixed between sampled and unsampled areas.

The contour plots of the seasonal mean of the surface soil moisture measurements illustrated the wet and dry areas that were present in each of the plots. The AL1 plot had two predominant wet areas ($\theta > 27\%$) in the northeast and southwest corners and a band of 24-27% volumetric water content measurements from the northwest corner to the southeast corner. In AL3, higher soil moisture contents (24-27%) were located on the eastern side of the plot while the center and western sides of the plot were slightly drier (21-24%). The plot AH3 exhibited a wet ($\theta > 27\%$) to dry ($\theta < 21\%$) pattern from the northwest corner to the southeast corner. Aside from the northwest corner of AH3, which had a small section of 27-30% soil moisture, the AH3 plot had relatively large areas of consistent soil moisture that ranged from 18-24% volumetric water content. Finally, the AL4 plot had the highest level of surface soil moisture variability of the plots with the average seasonal surface soil moisture measurements ranging from 15-30% volumetric water content. In each of the plots, there were areas that could be defined as wet or dry based on their average seasonal soil moisture.
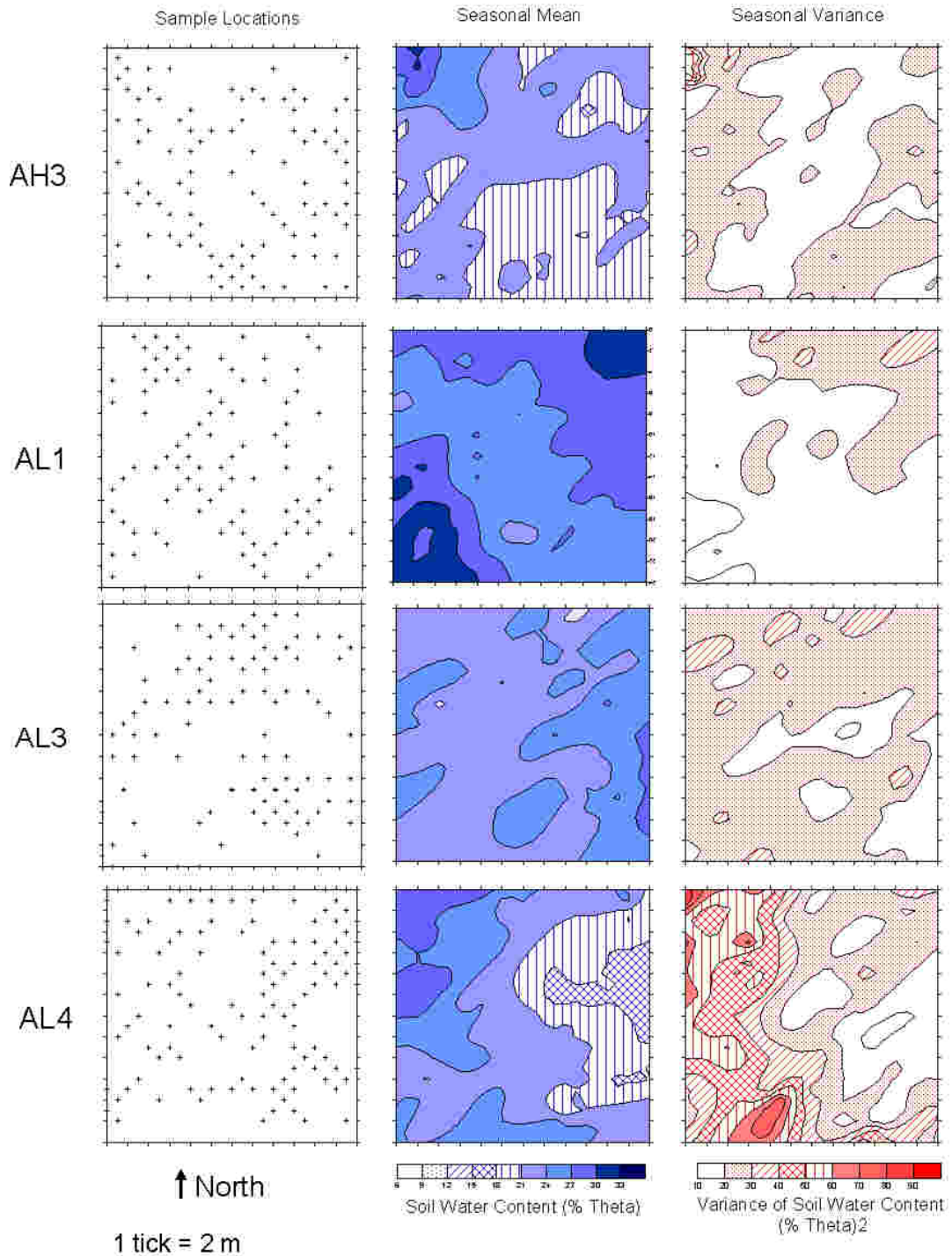
Figure 9. Sampling locations, seasonal means, and seasonal variances of the
volumetric surface soil moisture measurement for the AH3, AL1, AL3, and AL4 plots
for the 2000 growing season.

Contour plots of the variance of the seasonal soil moisture data demonstrated the spatial stability of the measurements within each plot (Figure 9). AL1 had the lowest levels of seasonal soil moisture variation of all 4 plots. Within the AL1 plot, the areas exhibiting the highest water contents had the most variation. In the AH3 and AL3 plots, the standard deviations observed in the AH3 and AL3 plots were higher than the AL1 plot. In AH3, the area of highest water content had the highest standard deviation. In AL3, the wettest area had a very low standard deviation indicating that the water contents remained high and varied only slightly throughout the season. The AL4 plot was the most variable of the 4 plots. The highest standard deviations were found in the wettest areas; however, the intermediate soil levels also had high standard deviations. The variance of the seasonal soil moisture values illustrated the changes or lack of changes of the soil moisture levels during the growing season.

The spatial distribution and variability of the surface soil moisture found in the 2000 plots indicates some of the variations present in the soils from this field. The classification of the soil type for this area was comprised of a mixture of soil series. The complex designation of soils indicates that changes in the physical properties of the soil occur over very short distances. The change in physical properties of the soil could be as a result of small scale changes in elevation, erosion, different parent material, or movement of material from adjacent areas. The distribution of surface soil moisture in these plots would reflect some of these subtle changes in the soil's properties. Unlike soil moisture sampled from a consistent soil mapping unit, the soils in complex mapping units would tend to have higher variation

due to the changes of the physical properties of the soil. The distribution and variation of the surface soil moisture observed in 2000 indicates the variation in the soils from this area.

CONTINUITY OF WATER CONTENTS – 2000

A measurement of continuity of the water content measurements observed in each plot was determined using an indicator variable based on the difference between the observed soil moisture and the mean value of the plot for that sampling period (Petrone et al 2003). The difference of the soil moisture calculations were plotted on contour plots with –1 representing a value less than the mean, zero representing the mean, and +1 representing a value exceeding the mean. The plots were constructed for each plot on each sampling date. (Figures 10-13) The contour plots were evaluated for soil moisture patterns that were persistent throughout the growing season.

Patterns of wet and dry areas of soil moisture were present in each of the plots during the sampling interval. The AH3 plot had a wet area (northwest corner) and a dry area (southeast corner) that were persistent in the contour plots throughout the growing season (Figure 10). The AL1 plot has consistently wet northeast and southwest corners and a drier band that ran across the plot from the northwest corner to the southeast corner. (Figure 11) The patterns of relative soil moisture levels in plot AL3 were not as continuous or well defined as in the other plots (Figure 12).

Patterns of AH3 Surface Soil Moisture
(-1 Below Mean or 1 Above Mean)

Figure 10. Spatial patterns of surface soil moisture in the AH3 plot during the growing season. Each measurement location was compared to the plot mean and an indicator value of -1 (below mean) or 1 (above mean) was assigned.

Patterns of AL1 Surface Soil Moisture
(-1 Below Mean or 1 Above Mean)
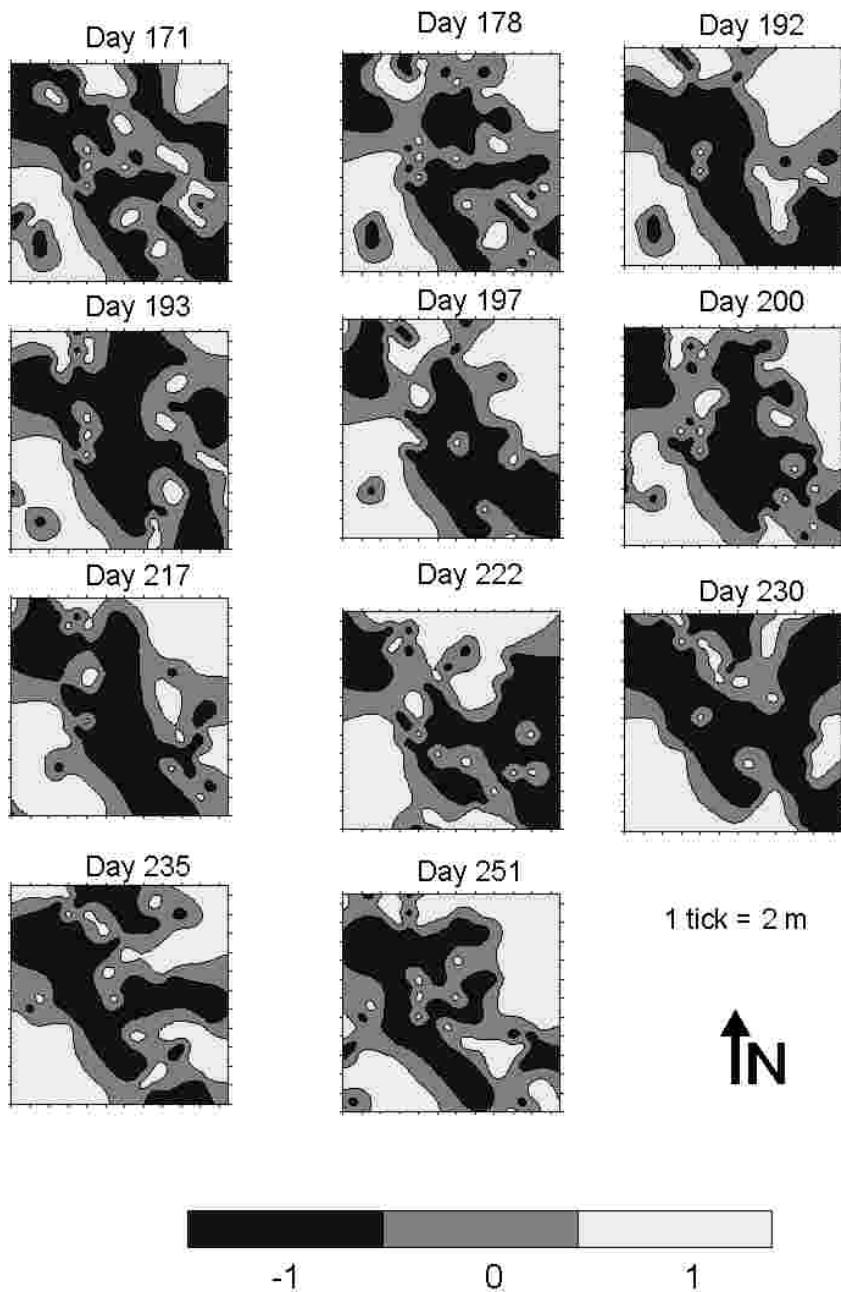
Figure 11. Spatial patterns of surface soil moisture in the AL1 plot during the growing season. Each measurement location was compared to the plot mean and an indicator value of -1 (below mean) or 1 (above mean) was assigned.

Patterns of AL3 Surface Soil Moisture
(-1 Below Mean or 1 Above Mean)
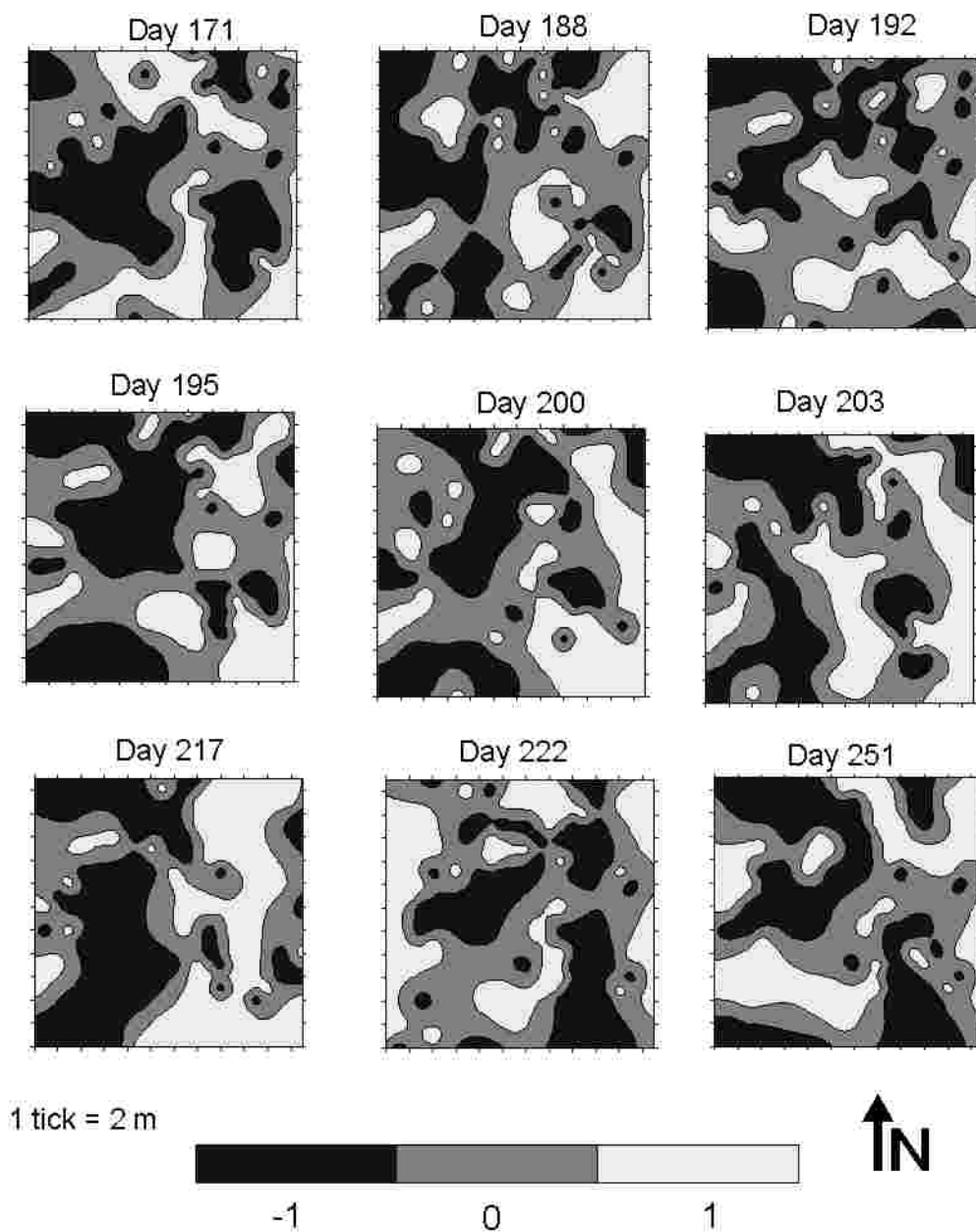
Figure 12. Spatial patterns of surface soil moisture in the AL3 plot during the growing season. Each measurement location was compared to the plot mean and an indicator value of -1 (below mean) or 1 (above mean) was assigned.

Patterns of AL4 Surface Soil Moisture
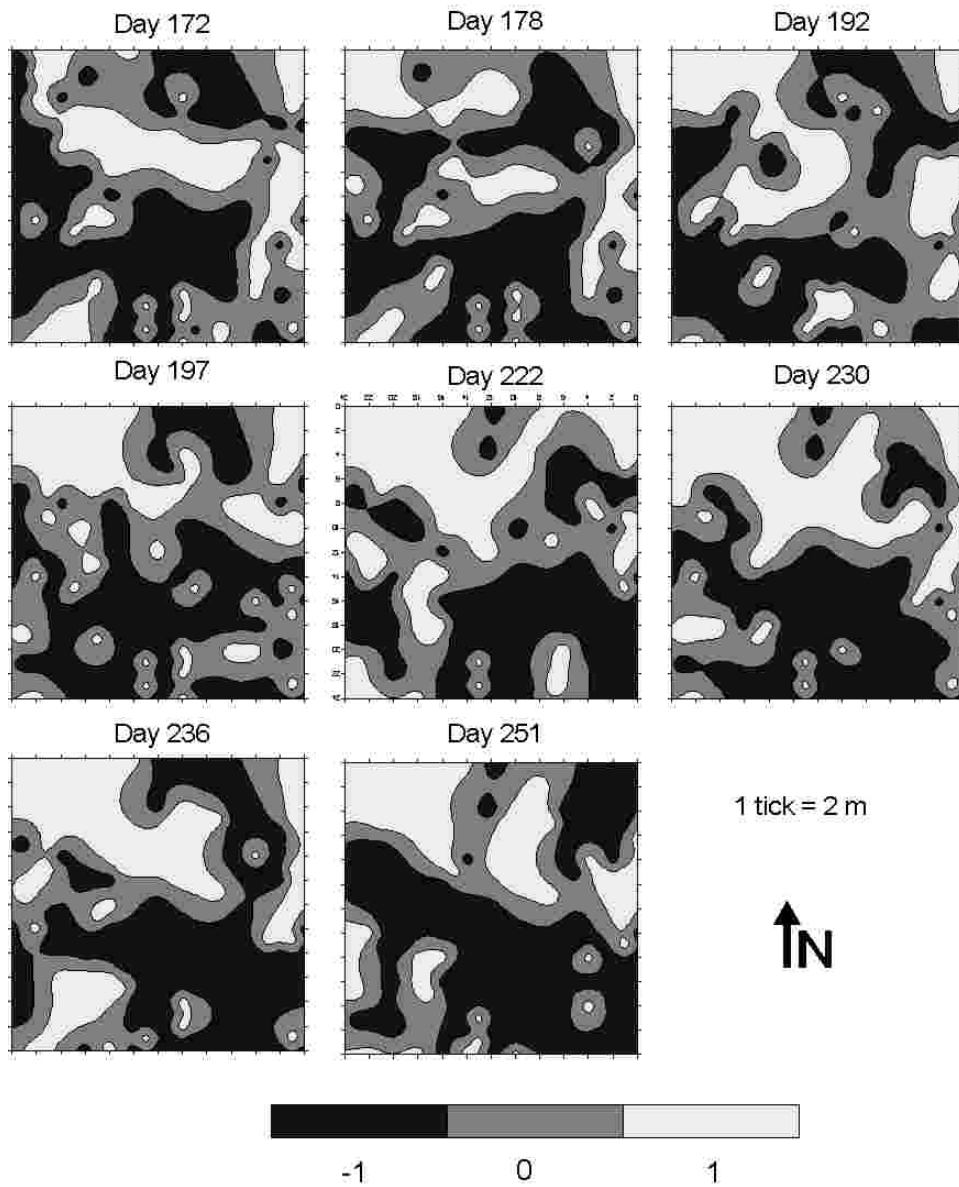## (-1 Below Mean or 1 Above Mean)
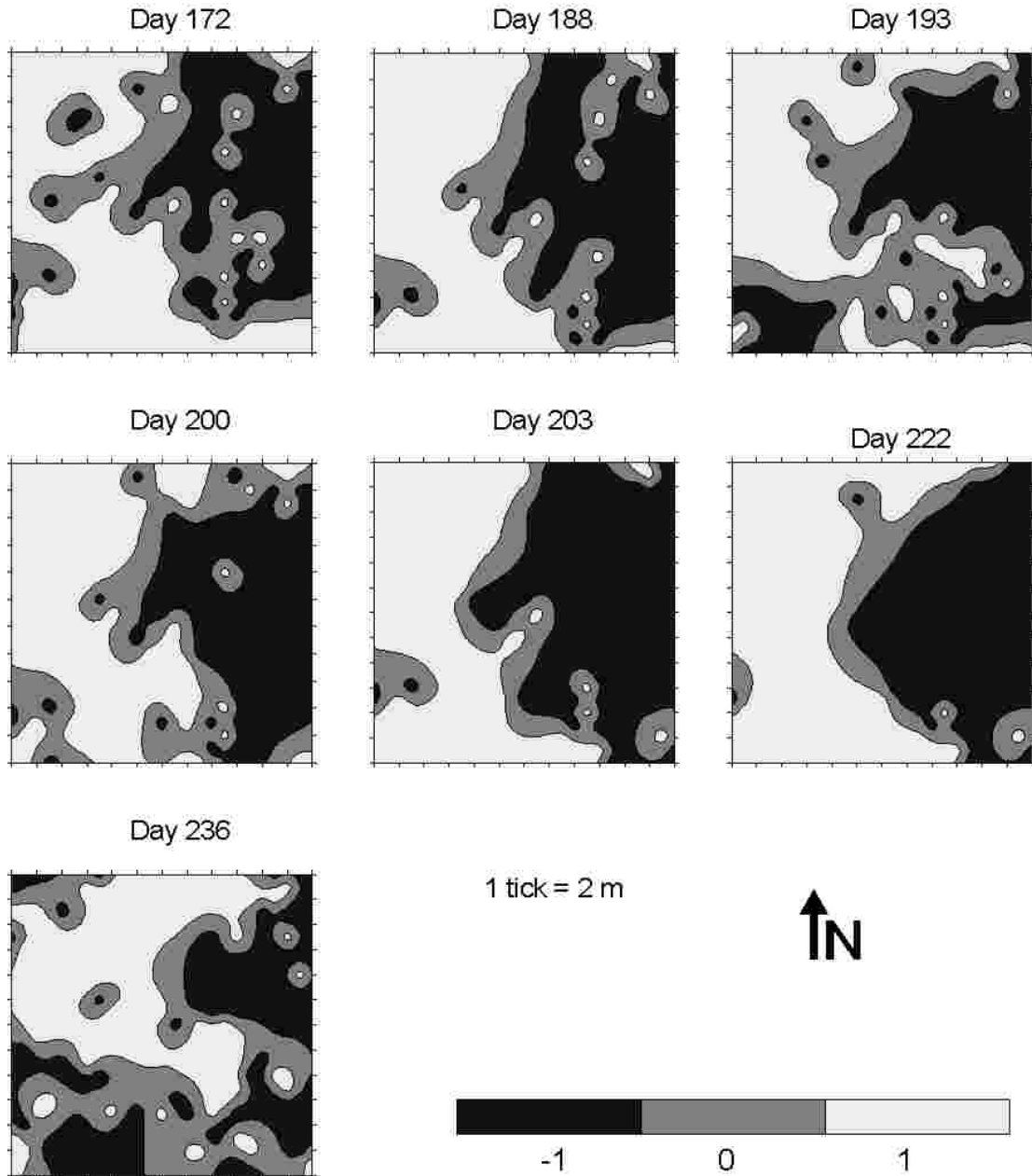
Figure 13 . Spatial patterns of surface soil moisture in the AL4 plot during the growing season. Each measurement location was compared to the plot mean and an indicator value of -1 (below mean) or 1 (above mean) was assigned.

Unlike the other plots, the soil moisture levels in AL3 did not vary dramatically and as a result, the observed soil moisture that fell above and below the mean was not consistent from sample date to sample date. Finally, the AL4 plot exhibited a moderate level of continuity despite the high variability within the plot. (Figure 13) The relative soil moisture patterns split the AL4 plot down the middle with wetter soil moisture on the west side and drier soil moisture on the east side. These results support the continuity of the surface soil moisture data within the plots and the ability to illustrate the patterns using an indicator variable.

TEMPORAL STABILITY OF THE INDIVIDUAL LOCATIONS - 2000

The temporal stability of each surface soil moisture sampling location was tested using the mean relative difference of the soil moisture data. The mean relative difference is the average difference between the plot mean and the observed soil moisture throughout the sampling interval. In Figure 14, the calculations of the mean relative soil moisture difference for each plot are sorted from the lowest to the highest value. The range of mean relative differences in plot AH3 (-0.44 to 0.73) and AL4 (-0.42 to 0.57) was higher than the plots AL1 (-0.26 to 0.33) and AL3 (-0.31 to 0.30).

The range of the mean relative differences indicates some variation between plots; however, most of the difference between the ranges is accounted for by the extreme values in each plot. The standard deviation of the mean relative difference, however, indicates a clear difference in the variation of the plots. The average standard deviation in plot AL4 (0.18) is significantly higher than AL1 (0.10), AL3 (0.11) and AH3 (0.13). The range and standard deviation of the mean relative

Mean Relative Difference of Observed Surface Water Contents By Location in 2000
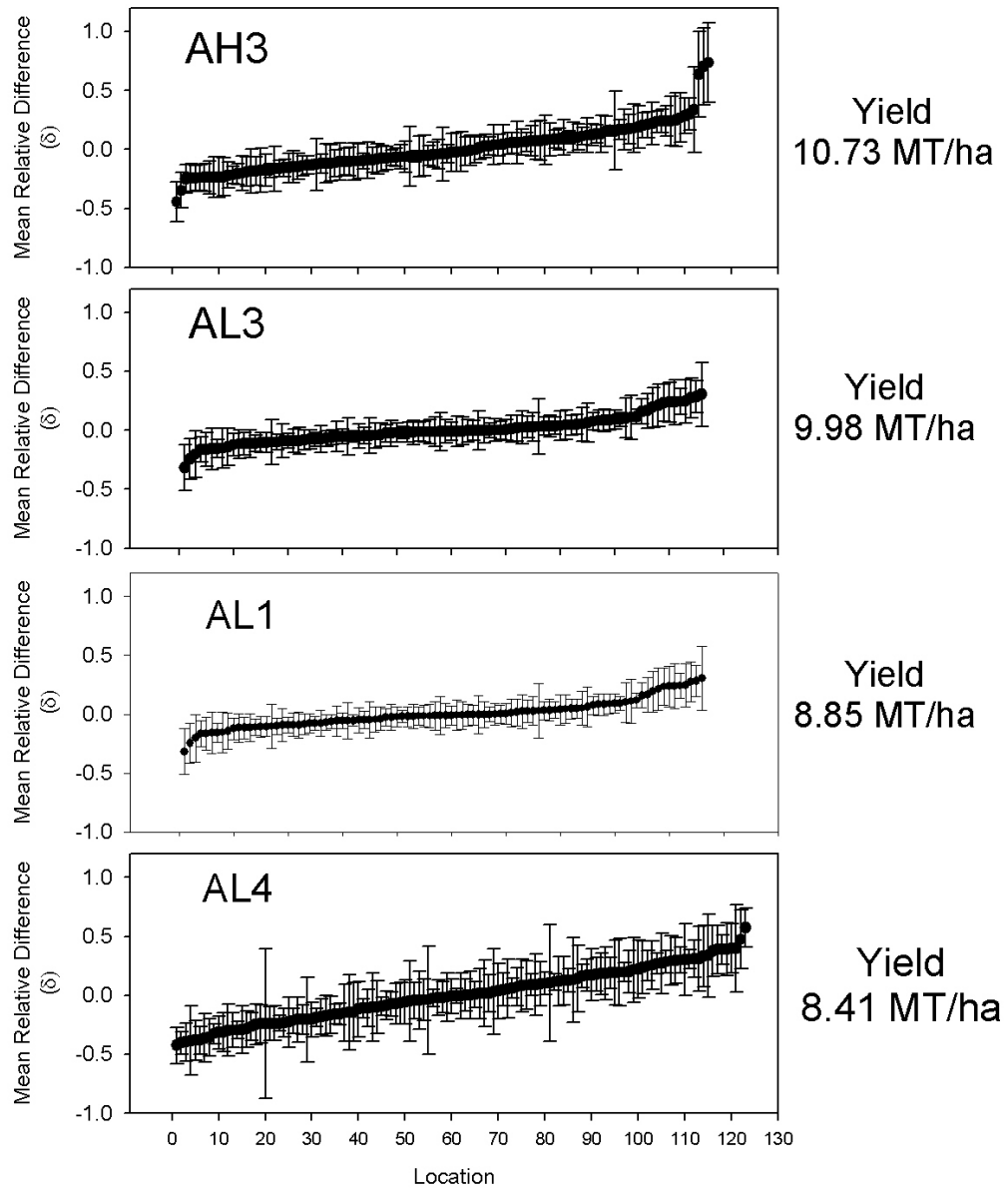
Figure 14. Rank order of the mean relative difference and standard deviations of the surface soil moisture data by location during the 2000 growing season.

difference of the surface soil moisture locations indicate that the temporal stability of the soil moisture measurements in the AL4 plot is much lower than the temporal stability found in the other three plots.

SURFACE SOIL WATER 2000– SEMI-VARIOGRAMS

The spatial relationships present in the surface soil moisture data in 2000 were tested using semi-variograms. Sample semi-variograms were calculated and fitted using spherical semi-variogram models for each plot on each sampling date (Figures 15-18). The omni-directional spherical models estimated the shape of the sample semi-variograms in 3 of the 4 plots. In the AL4 plot, the omni-directional search window produced a sample semi-variogram that continued to rise throughout the sampling distance and did not exhibit a definitive sill value. Sample semi-variograms that fail to reach a sill value indicate that the variation between samples continues to increase beyond the range of sample data. Factors such as elevation or changing soil texture could produce an increasing variogram without a sill at short distances (<100m), and as a result, the omni-directional data could not be modeled using a spherical model. For the AL4 plot, an anisotropic sample semi-variogram was calculated using a 90-degree search window oriented in a north-south direction. The results of the anisotropic search window produced a directional sample semi-variogram with a sill that could be fitted using a spherical model. The spatial relationships in each plot were compared using the nugget, sill, and range values of each of the fitted models. (Table 2)
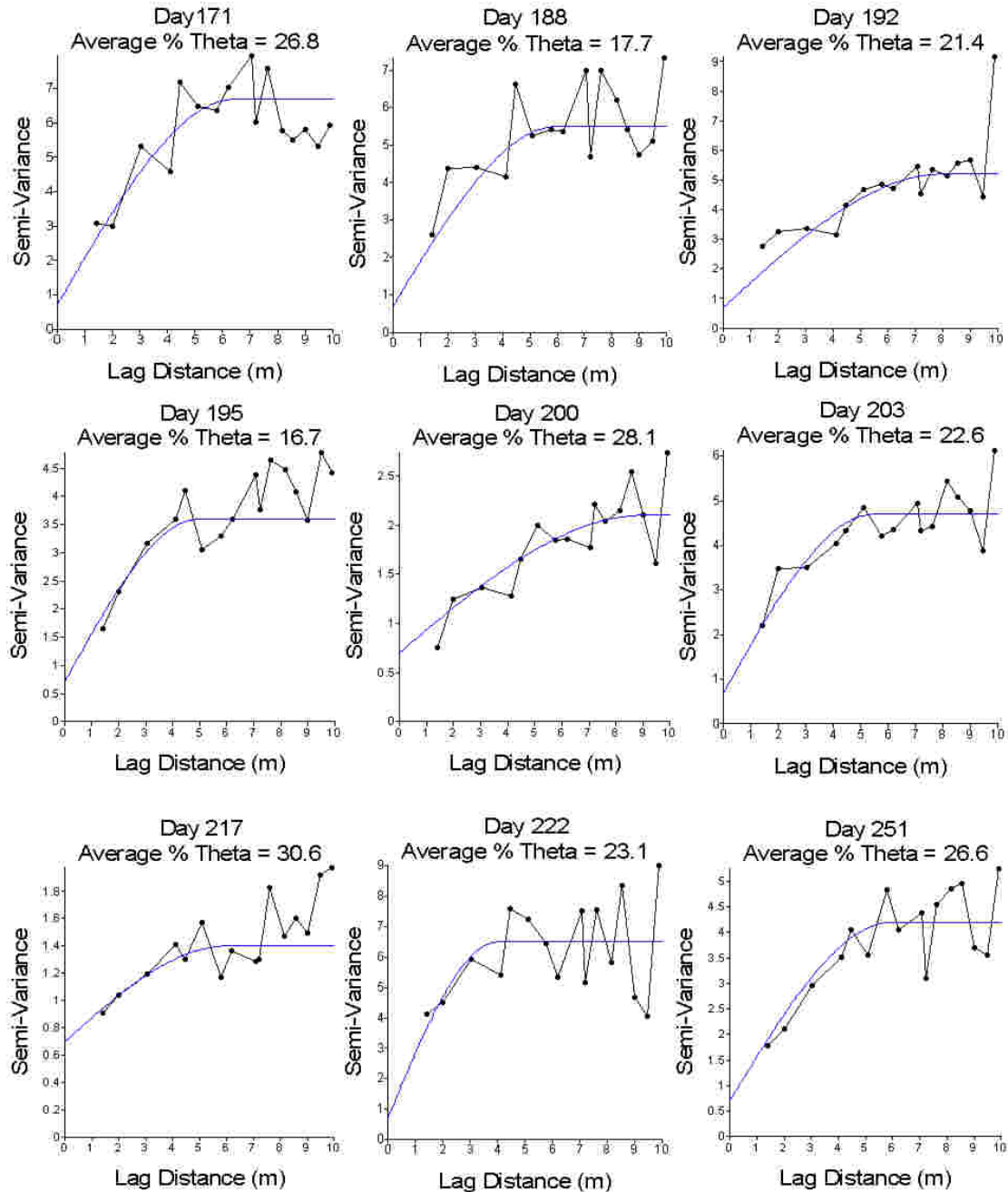
Figure 15. Semi-variance $(cm^3/cm^3)^2$ plotted versus lag distance for omni-directional sample (black line with dots) and fitted theoretical (blue line) spherical semi-variogram models for each day that the surface soil moisture data was collected in Plot AL3 during the 2000 growing season.
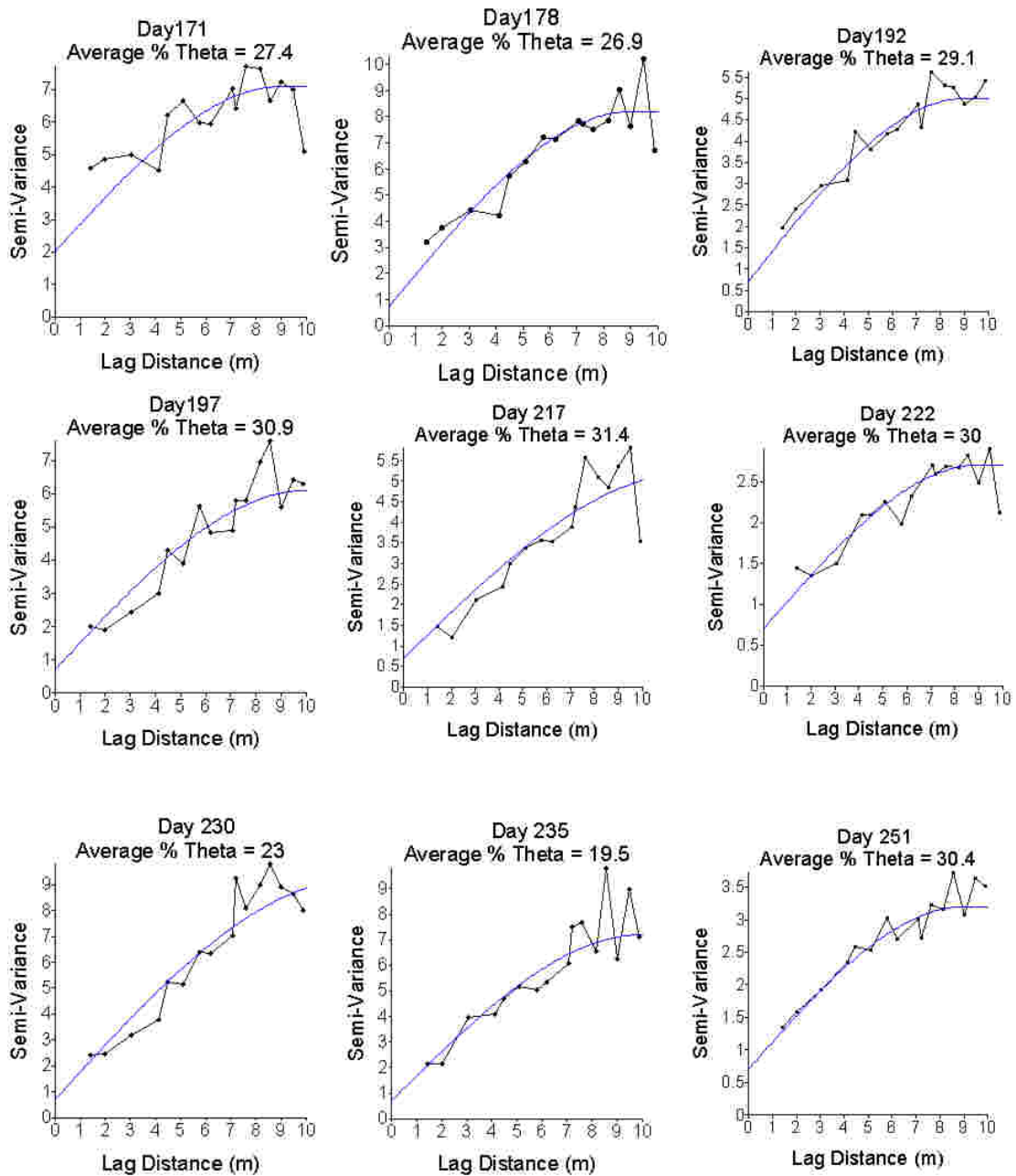
Figure 16. Semi-variance $(cm^3/cm^3)^2$ plotted versus lag distance for omni-directional sample (black line with dots) and fitted theoretical (blue line) spherical semi-variogram models for each day that the surface soil moisture data was collected in Plot AL1 during the 2000 growing season.

Figure 17. Semi-variance $(cm^3/cm^3)^2$ plotted versus lag distance for anisotropic sample (black line with dots) and fitted theoretical (blue line) spherical semi-variogram models for each day that the surface soil moisture data was collected in Plot AL4 during the 2000 growing season. The search window was oriented North/South and the search window was 90 degrees.
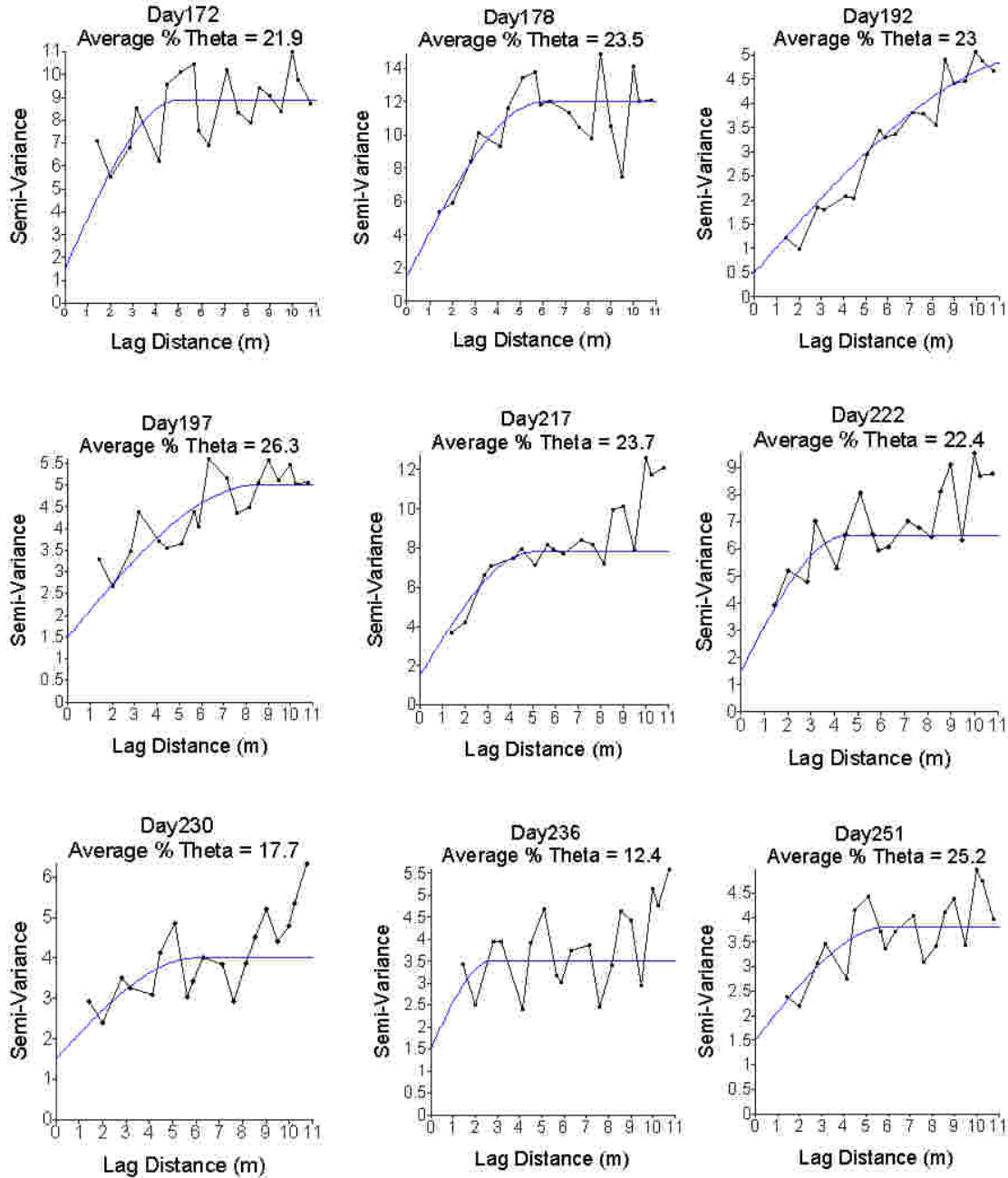
Figure 18. Semi-variance (cm^3/cm^3)^2 plotted versus lag distance for omni-directional sample (black line with dots) and fitted theoretical (blue line) spherical semi-variogram models for each day that the surface soil moisture data was collected in Plot AH3 during the 2000 growing season. ariograms are spherical models.

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Table 2. Parameters of the theoretical spherical semi-variogram models fitted to the surface soil moisture data for the 2000 growing season.

Plot	Day	Nugget	Sill	Range (m)	Total Variance	Water Content	Anisotropic
AL4	172	0.005	0.115	8	0.12	0.233	Yes
	188	0.005	0.085	8.5	0.09	0.211	Yes
	193	0.005	0.1	9	0.105	0.177	Yes
	200	0.005	0.087	8.5	0.09	0.254	Yes
	203	0	0.054	10	0.054	0.267	Yes
	222	0.005	0.08	9	0.085	0.27	Yes
	236	0.005	0.048	4.8	0.053	0.128	Yes
AH3	172	0.015	0.074	5	0.089	0.219	No
	178	0.015	0.105	6	0.12	0.235	No
	192	0.005	0.045	13	0.05	0.23	No
	197	0.015	0.035	10	0.05	0.263	No
	217	0.015	0.063	5	0.078	0.237	No
	222	0.015	0.05	4.5	0.065	0.224	No
	230	0.015	0.025	6	0.04	0.177	No
	236	0.015	0.02	2.7	0.035	0.124	No
	251	0.015	0.023	6	0.038	0.252	No
AL3	171	0.007	0.06	6.5	0.067	0.268	No
	188	0.007	0.048	6	0.055	0.177	No
	192	0.007	0.045	8	0.052	0.214	No
	195	0.007	0.029	5	0.036	0.167	No
	200	0.007	0.014	9	0.021	0.281	No
	203	0.007	0.04	5.5	0.047	0.228	No
	217	0.007	0.007	6	0.014	0.306	No
	222	0.007	0.058	4	0.065	0.231	No
	251	0.007	0.035	6	0.042	0.266	No
AL1	171	0.02	0.051	9	0.071	0.274	No
	178	0.007	0.075	9	0.082	0.269	No
	192	0.007	0.043	9	0.05	0.291	No
	197	0.007	0.054	10	0.061	0.309	No
	217	0.007	0.045	12	0.052	0.314	No
	222	0.007	0.02	9	0.027	0.3	No
	230	0.007	0.085	12	0.092	0.23	No
	235	0.007	0.065	10	0.072	0.195	No
	251	0.007	0.025	9	0.032	0.304	No

The nugget values for the 2000 plots ranged from 0 to 0.02 $(cm^3/cm^3)^2$. Previous studies have found that the estimations of the nugget can be unreliable primarily due to a lack of data. (Western et al.; 1999) For this part of the study, the nugget value is small compared to the overall variance observed in the system. Since the impact of the nugget value does not significantly change the overall variance of the system, discussions on the nugget value will not be separated from discussions on the overall variance of the system.

The average sill values for the fitted semi-variograms were 0.081 $(cm^3/cm^3)^2$ for AL4, 0.0489 $(cm^3/cm^3)^2$ for AH3, 0.0373 $(cm^3/cm^3)^2$ for AL3, and 0.0514 $(cm^3/cm^3)^2$ for AL1. The sill values appear to change in response to the water content. Dry conditions ($< 0.15 \ cm^3/cm^3$) or very wet ($> 0.27 \ cm^3/cm^3$) conditions resulted in lower variance levels and smaller sill values. Intermediate water contents between 0.20-0.27 cm^3/cm^3 produced the highest sill values and highest overall variance levels for the plots.

The average range values for the 2000 semi-variogram calculations were less than 10 m for all of the observed soil moisture plots and indicates a typical level of variability observed within the surface soil moisture data. Plots AL3 (6.2 m) and AH3 (6.4 m) had similar average range values. Plots AL4 (8.25 m) and AL1 (9.8 m) had slightly longer average range distance. The ranges of spatial dependence in the surface soil moisture data are consistent with findings by Greminger et al (1985) who observed spatial structure in water content values up to 10 m.

There were some variations in the ranges between sampling dates; however, the cause of the variations appear to be related to the average water contents of the

plots and the variability of the soil moisture distribution. In every plot, the range increased between the lowest and highest water content readings. At intermediate soil moisture values, the relationship between range and water content varied and was not as well defined. Redistribution of water after a rainfall, uneven drying conditions, and plant uptake contributed to the spatial variability of the surface soil moisture at the intermediate soil moisture conditions. These observations are consistent with work by Blackmore et al. (1999) who found that within field variation of soil moisture and its association to water holding capacity was a major contributing factor to differences in yields. The high variability at the intermediate soil moisture levels was reflected in the semi-variogram calculations. Some of the variation associated with the range estimations could be associated with sill identification. Of the semi-variogram components, the range distances appear to have a higher level of temporal stability compared to the sill values over the duration of the growing season.

SOIL TESTING – 2000 PLOTS

Soil testing (University of Maryland Cooperative Extension Service Soil Testing Lab) in 2001 determined the soil nutrient and physical properties of the soil moisture plots (Table 3). Soil textural analysis indicated the soils within the plot areas were either sandy loams (AH3, AL3, AL4) or silt loams (AL1). Soil pH ranged from 6.3 to 7.0 and was within the acceptable range for corn crop growth and nutrient availability in all of the plots. In plots AL4 and AH3, there was a higher organic matter concentration than in plots AL1 and AL3. The results of the other nutrient tests were qualitatively evaluated using an interpretive classification table provided by the University of Maryland Soil Testing Lab.

Table 3.   Nutrient analysis results from University of Maryland Soil Testing Lab for soil samples from 0-30 cm taken in 2001

PLOT	pH	Magnesium (kg/ha) Mg	Phosphorus (kg/ha) P_2O_5	Potassium (kg/ha) K_2O	Calcium (kg/ha) Ca	Organic Matter (%)	Texture
AH3	6.4	128	301	81	133	3.6	SL
AH3	6.6	129	327	101	141	2.7	SL
AL1	7.0	129	292	149	196	2.4	SiL
AL3	6.3	96	130	79	77	2.0	SL
AL4	6.3	129	371	105	126	3.2	SL
AL102	6.9	123	345	115	149	2.3	SL
AL102	7.0	114	279	110	196	2.5	SiL
AL402	6.6	129	168	85	180	3.3	SiL
AL402	6.5	116	193	66	125	3.0	SiL

The magnesium, phosphorus, calcium, and potassium levels were analyzed and classified according to the recommendations for corn crop growth.   The magnesium levels were 96-129 kg/ha Mg, which fell within the medium category, 79-139 kg/ha, of the classification table. The phosphorus levels in the plots ranged from 130-371 kg/ha P_2O_5 and were considered optimum, 115-230 kg/ha P_2O_5, to excessive >230 kg/ha P_2O_5. All of the plots were classified into the low category for calcium (0-481 kg/ha Ca); the test results ranged from 77-196 kg/ha Ca. The potassium levels

were split into low (40-94 kg/ha K_2O) and medium categories (95-179 kg/ha K_2O). Plot AL3, 79 kg/ha K_2O, was classified as low potassium while AL1, 149 kg/ha K_2O and AL4, 105 kg/ha K_2O, fell into the medium category. Plot AH3 was split between both potassium categories; one sample was considered medium, one was considered low. The soil testing results indicated slight variations between plots that are consistent with the mapping units and soil variability within Section A.

The soil test results are consistent with the management practices of the field. The high soil P levels are most likely attributable to the continual use of digested dairy manure fertilizer. Manure fertilizers when applied to supply nitrogen needs for corn tends to provide excessive amounts of phosphorus and can lead to high soil phosphorus levels in only a few years of use. The calcium and potassium levels are comparable with soils in the Beltsville region that have similar sandy soil textures. The magnesium, phosphorus, calcium, and potassium portions of the soil test results indicate that the potential for plant growth attributed to soil fertility does not appear to be significantly different between the plots. The potential for plant growth is important to the soil moisture measurements because the soil moisture could be influenced by canopy size. For this portion of the soil test, the similar nutrient concentrations indicate that the potential plant canopy size would be expected to be approximately equal and as a result, the impact on the soil moisture levels from these nutrients should not be significant.

The nitrogen fertilizer in Section A was applied at a rate that should not have limited average corn growth and production. The soil nitrogen levels were tested after planting; and the sidedress application rate for Section A was adjusted based on

the soil test results and the production goals of the field. Under average growing conditions, the corn crop will use nitrogen at a rate slightly below the application rate. However, under optimum conditions, the corn crop's nitrogen use could exceed the application rate at which point the spatial distribution of soil nitrogen become very significant for plant growth and production. Another concern with optimum growing conditions is leaching. The additional soil moisture could leach the soil N from the soil before the corn plants can uptake it for growth. The spatial distribution of soil nitrogen, instead of soil moisture, could become the predominant limiting growth factor in corn crop production during optimum growing conditions. With high rainfall amounts during the 2000 growing season, the soil moisture would be expected to be less of a growth-limiting factor than during an average rainfall year and the nutrient concentration would be expected to be more of a limiting factor.

YIELD DATA – 2000

The observed 2000 corn grain yields in all of the plots exceeded the expected production values described in the NRCS Beltsville Agricultural Research Center Special Soil Report (1995). The report's predictions were 6.27-7.53 MT/ha and were based on the predominant soil-mapping units found in each plot. The observed corn grain yields in the plots were 10.73 MT/ha for AH3, 9.98 MT/ha for AL3, 8.85 MT/ha for AL1, and 8.41 MT/ha for AL4. The highest yields (AH3 and AL3 plots) were located in the center of the field. The AL1 plot, located slightly to the southeast of the center of the field, and the AL4 plot, which was located on the edge of the southwestern part of the field, produced approximately 20% less. The spatial distribution of the yields indicates the production variability that occurred in each of

the plots. (Figure 19) The higher yielding plots, AL3 and AH3, had ranges of 3.20-15.13 MT/ha and 5.77-12.81 MT/ha, respectively. The AL1 plot had a range of 3.83-11.86 MT/ha. The AL4 plot with the lowest average production had the largest range with observations between 1.63-16.88 MT/ha. The average observed yields and ranges of corn production for 2000 were much higher than was expected for this field.

Sample semi-variograms were calculated and theoretical semi-variogram models were fit for the yield data for 2000 in Section A. The range of the spatial dependence was found to be 40 m and the total variance (sill + nugget) in 2000 was 138 $(MT/ha)^2$ (Figure 20). The spatial relationships within the yield data are a direct result of the growing conditions present within the field during the 2000 growing season including the soil moisture levels and the available nutrient levels.

The relationship between the surface soil moisture patterns and the distribution of yields for the 2000 growing season was not clear due to the high levels of variation in both datasets. In plots AL3, AL4, and AH3, the mean relative difference of the surface soil moisture data plotted against the yield data resulted in a wide distribution of points that lacked any perceivable relationship. Previous studies have found that direct relationships between yield and surface soil moisture can be adversely affected by additional factors including nutrient concentrations and small scale variations in elevation (Cavero et al., 2001; Kravchenko and Bullock, 2000).

Contour Plots of 2000 Yield Data Within Each Soil Moisture Plot.
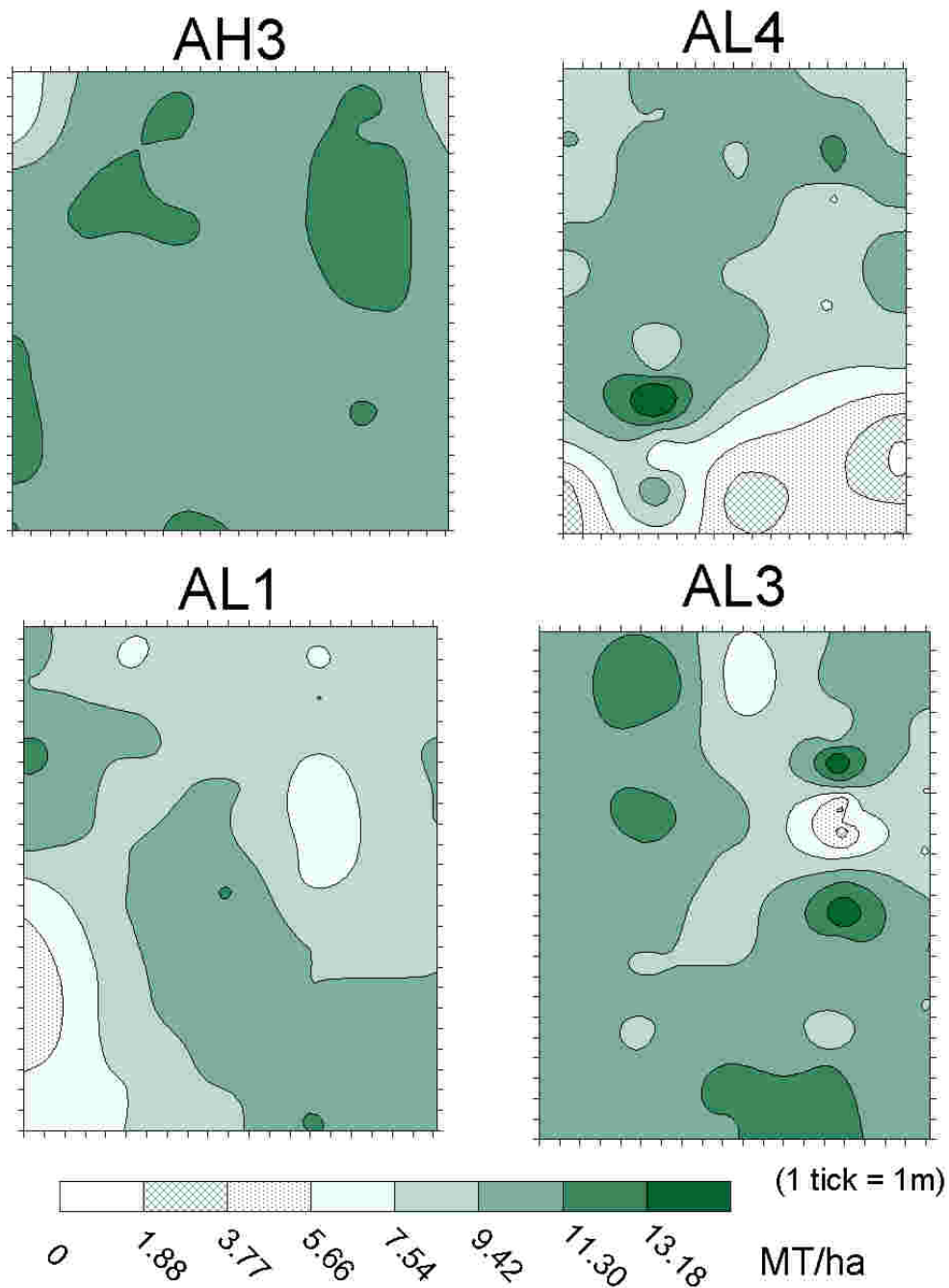
Figure 19. Contour maps of the corn yield data collected from plots AH3, AL4, AL1, and AL3 during the 2000 growing season.

Semi-variogram plots for the Yield Data in Section A.
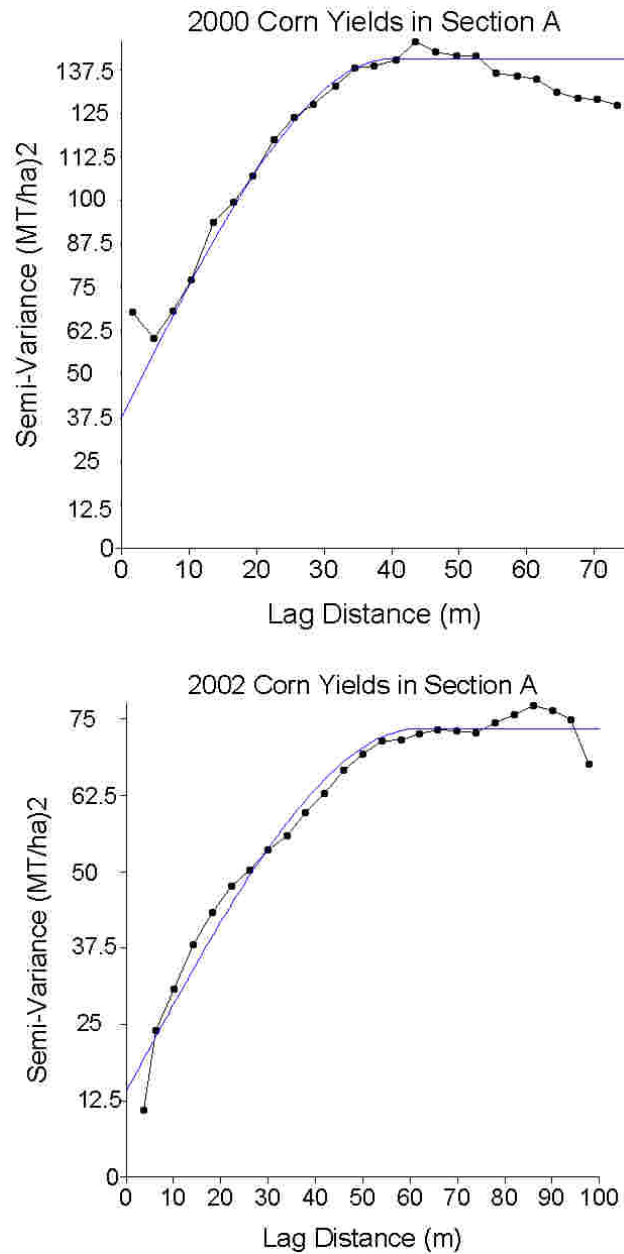
Figure 20. Omni-directional sample (black line with dots) and fitted theoretical (blue line) spherical semi-variogram models for the corn yield data collected in 2000 and 2002 from Section A of OPE3.

Areas of high and low production did not coincide consistently with the patterns of surface soil moisture. In the AL1 plot, however, there appeared to be a relationship between the yield data and the patterns of soil moisture. The higher yield values in AL1 coincided with the soil moisture values below the mean while the lower yield values were associated with the higher soil moisture levels. The AL1 plot represented higher soil moisture levels and lower variation than the other plots which could explain the inverse soil moisture to yield relationship; however, the lack of relationships in the other plots suggests that the small scale variability in soil moisture and yield is too high to determine a definitive small scale relationship between the two variables for the 2000 growing season.

PRECIPITATION - 2002

The 2002 growing season was much drier than the 2000 growing season. Rainfall quantities in 2002 were 5.6 cm in June, 6.1 cm in July, and 6.4 cm in August. These values were lower than the average monthly rainfall in Beltsville by 39% in June, 41% in July, and 32% in August (Maryland's State Climatologist's Office). Compared to the observed rainfall during 2000, the 2002 season had 51% less precipitation for the combined months of June, July, and August. The reduced amounts of rainfall in 2002 were distributed relatively evenly throughout the season (Figure 21). The precipitation during the 2002 growing season resulted in lower soil moisture values than the 2000 growing season.

During the 2002 sampling period (Day 156-Day 227), there were 7 intervals without rain that exceeded 4 days. Three of the intervals were 4-6 days and started

on Days 152, 158, and 209. Three slightly longer dry periods of 7-10 days were observed starting with Days 171, 180, and 196. The longest dry period was 22 days starting on Day 218. From Day 209-239, only three days (215-217) recorded any rainfall.

Rainfall Quantities BARC Summer 2002
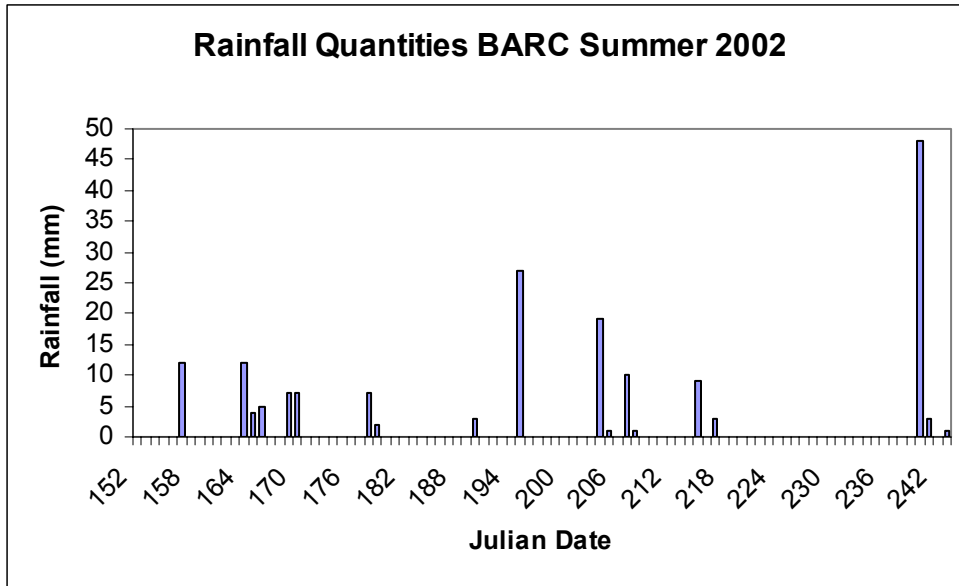
Figure 21. Daily rainfall quantities in millimeters recorded in Beltsville, MD during the 2002 growing season. The 2002 data was collected from a Campbell weather station mounted in Section B of the OPE3 field.

SURFACE SOIL MOISTURE 2002

The observed soil moisture measurements during the 2002 growing season reflected the lower rainfall quantities and were much lower than in 2000. The surface soil moisture means for the two plots ranged from 4.5% to 19% and remained around 10% for the majority of the growing season (Figure 22). The AL102 plot was slightly wetter by 3-5% than the AL402 plot throughout the sampling period. In the final

Average Surface Soil Moisture Observed in
Each Plot by Sampling Date in 2002
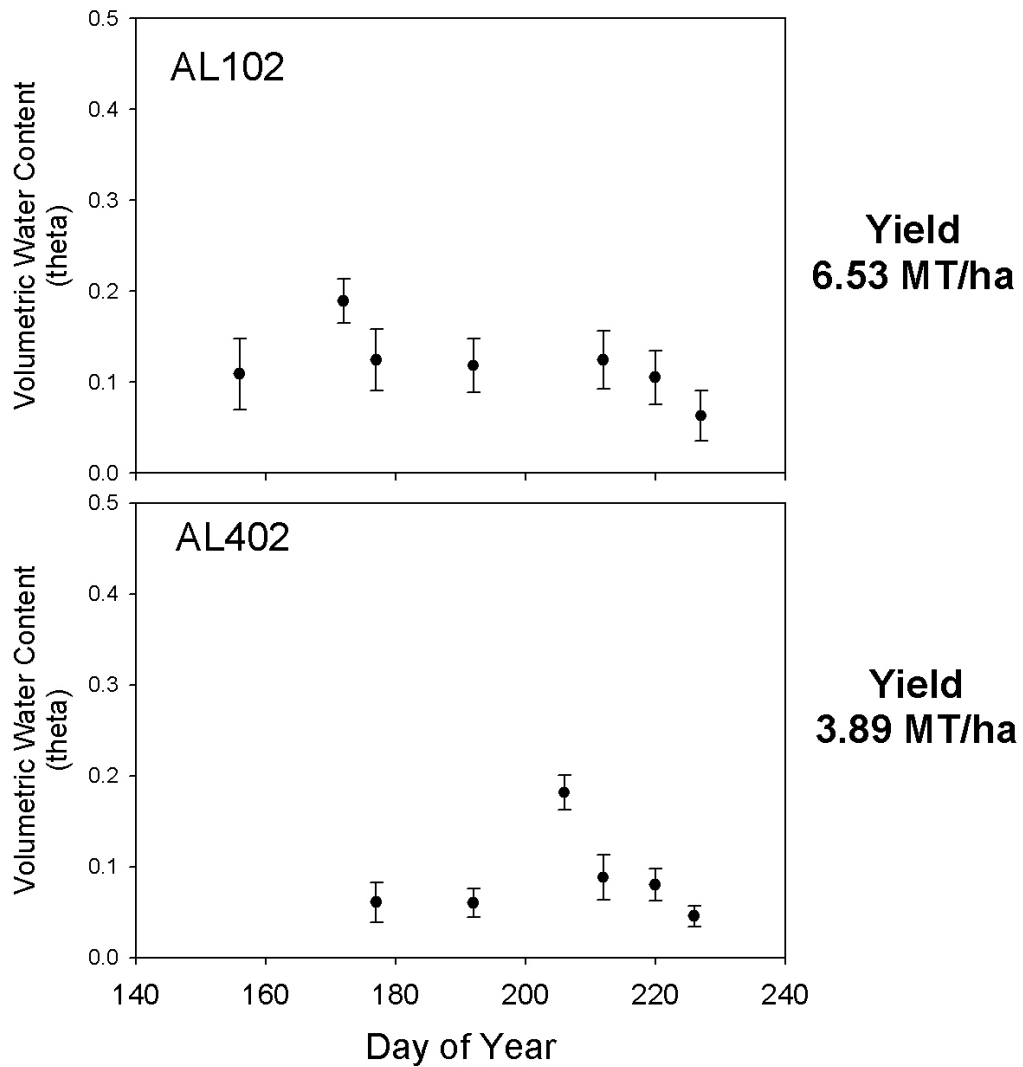
Figure 22. The average surface soil moisture in each of the 2002 plots throughout the season with the daily changes in standard deviations.

portion of the sampling interval, both plots had significant decreases in soil moisture associated with the dry period from July 27 - August 26 (Days 209-239).

The 2002 contour plots of the average seasonal surface soil moisture describe the lower moisture conditions that were present compared to the 2000 growing season. Although the soil water was reduced, the 2002 contours of similar soil moisture appear to be a comparable size to the 2000 data (Figure 23). Although the sizes of the contours were approximately equal, the 2002 data appeared to be more diversely distributed and not as continuous as observations in 2000. The diverse structure would not be unexpected since drying of the surface soil would not occur consistently and would depend on several factors including vegetation, climate, and soil properties. The diverse structure of the surface soil moisture exists in both the mean and variance contour plots for the AL102 and AL402 plots. The 2002 contour plots of the seasonal mean of the surface soil moisture indicate that, compared to the 2000 data, the soil was drier, with smaller areas of consistent water, and similar amounts of variation.

The soil properties of the 2002 plots contributed to the distribution of the surface soil moisture. Similar to the 2000 plots, the 2002 plots were located on highly variable soils. Since the overall soil moisture conditions were drier in 2002, the variability of the soil properties and its impact on the soil moisture conditions at individual locations could only be separated from the overall soil moisture conditions present in the system for the extreme cases. Significant changes in clay content or localized depressions are two examples of these extreme cases. Similar to the 2000

growing season, the surface soil moisture data observed in 2002 was impacted by the variations present in the soil's properties.

CONTINUITY OF WATER CONTENTS – 2002

Contour plots of the patterns of the 2002 soil moisture data demonstrate the changes to the continuity of the surface soil moisture during dry conditions. Similar to the 2000 data, an indicator variable was used to construct contour plots of the difference between the observed soil moisture content at the sampled locations and the average soil moisture content for the plot during the sampling interval. Observed soil moisture above the mean was defined as a 1, while soil moisture below the mean was designated a –1. Mean soil moisture values were classified as 0. For the AL1 plot, the contour maps of the indicator variable started as large polygons early in the season (Figure 24). As the season progressed, the polygon size was reduced and the pattern became oriented with the row direction. In AL4, the north-south orientation of the pattern was also evident but the polygon size remained larger throughout the season (Figure 25). The last three sampling dates for both plots fell within the 22-day dry period. The results from these sampling dates illustrate the drying pattern of the surface soil moisture. The high variability in both plots resulted in an interpolation that changed from a gradual pattern of contours during wet soil moisture conditions to a set of isolated regions during dry soil moisture conditions.

2002 Growing Season Surface Water Contents

Seasonal Mean

Seasonal Variance

AL1
2002

AL4
2002

6 9 12 15 18 21 24 27 30 33
Soil Water Content (% Theta)

1 tick = 2 m

10 20 30 40 50 60 70 80 90
Variance of Soil Water Content (% Theta)2

↑ North
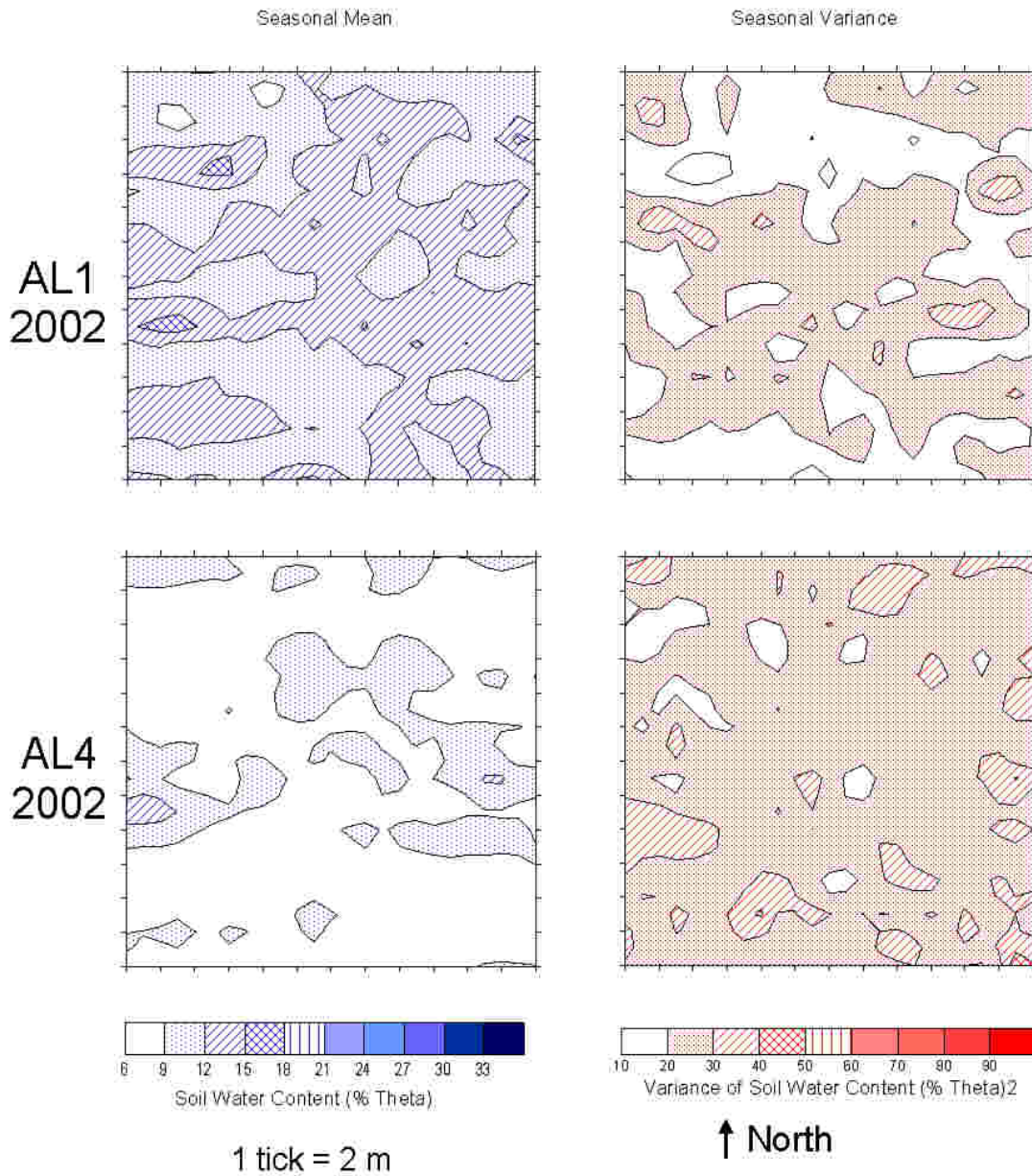
Figure 23. Contour plots of the seasonal means and variances of the surface soil moisture data sampled in the Al102 and AL402 plots for the 2002 growing season.

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Patterns of 2002 AL1 Surface Soil Moisture
(-1 Below Mean or 1 Above Mean)
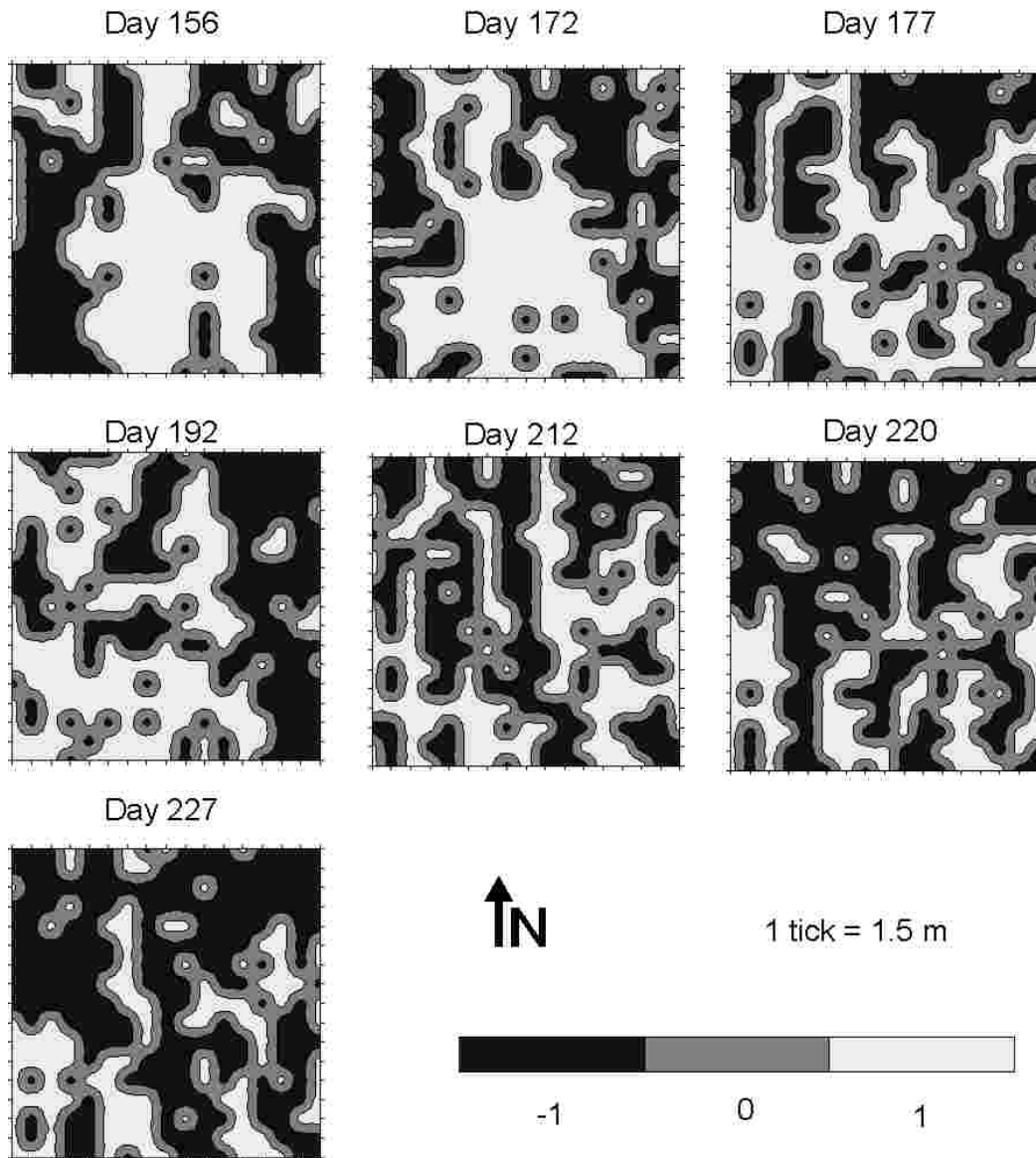
Figure 24. Spatial patterns of surface soil moisture in the AL102 plot during the 2002 growing season.

Patterns of 2002 AL4 Surface Soil Moisture
(-1 Below Mean or 1 Above Mean)

Day 177   Day 192   Day 206

Day 212   Day 220   Day 226

N

1 tick = 1.5 m

-1   0   1
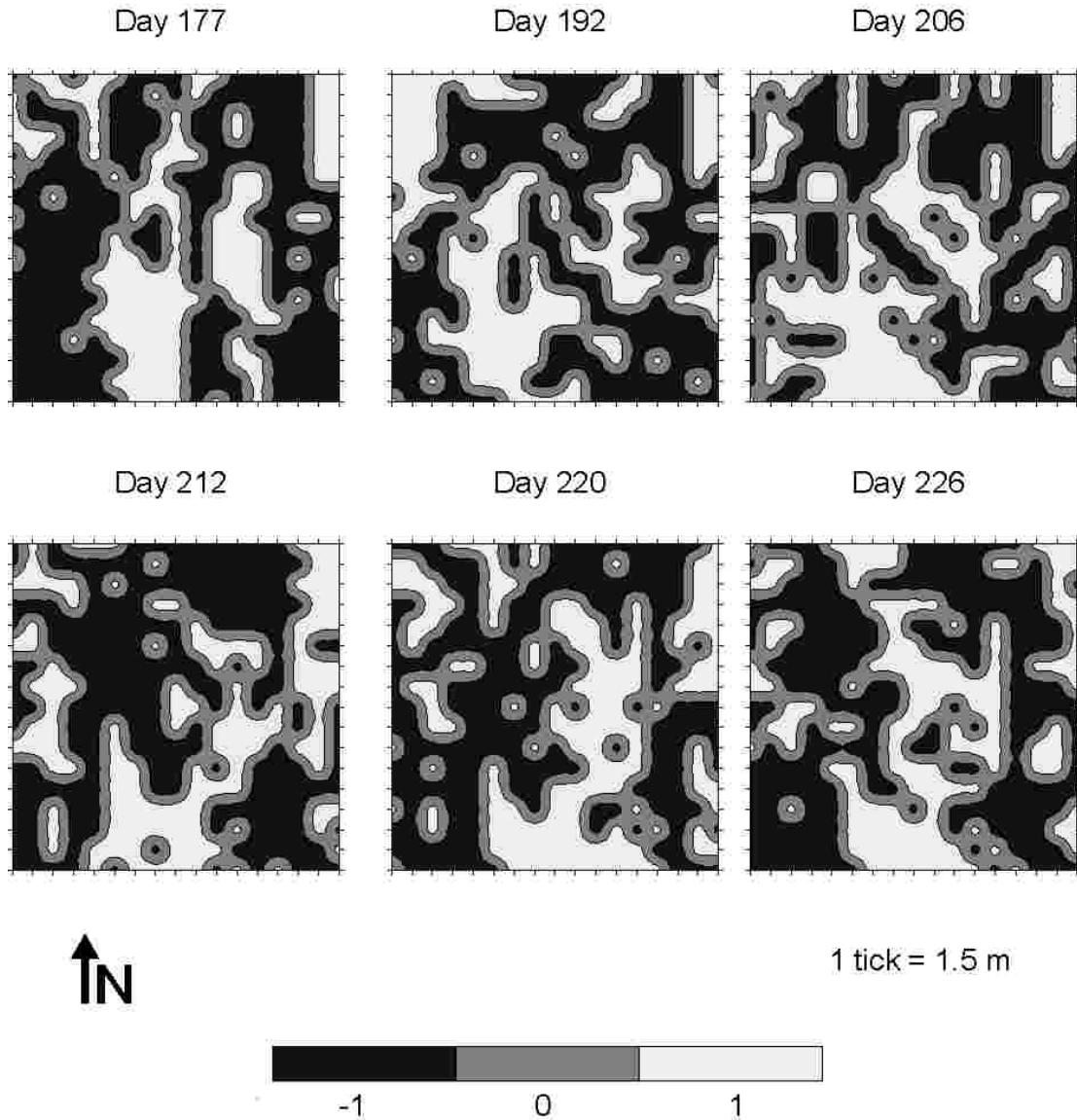
Figure 25. Spatial patterns of surface soil moisture in the AL402 plot during the 2002 growing season.

TEMPORAL STABILITY OF WATER CONTENTS – 2002

Analysis of the temporal stability of the surface soil moisture locations using the mean relative difference exhibited similar characteristics as the 2000 growing season. The range of the mean relative difference for AL402 was –0.28 to 0.87 while AL102 is -0.40 to 0.87 (Figure 26). The plot AL4/AL402 mean relative difference ranges decreased 15% between 2000 and 2002. Considering the difference in growing conditions between the two seasons, the change in the AL4/AL402 mean relative difference is not very high and it indicates that there is stability in the relative water contents observed in the AL4/AL402 area of the field over wet and dry conditions. On the other hand, in AL1/AL102, the mean relative difference range increased by 55%. The increase in mean relative difference indicates that the variability of the relative water contents has gone up dramatically from the 2000 growing season. Da Silva et al (2001) found temporal stability of soil moisture were closely related to stable soil properties such as texture and organic matter. The change in surface soil moisture's mean relative difference range between the two years may be as a result of differences in soil properties in the sampling areas. Although the change between years of the distribution of the mean relative difference was considerably different for the plots, the variability of the mean relative difference of the surface soil moisture between plots sampled in the 2002 growing season was not very high.   The reduced rainfall quantities resulting in lower soil moisture measurements could explain the lack of difference between mean relative difference of the surface soil moisture in the plots during the 2002 season.

Mean Relative Difference of Observed Surface Water Contents By Location in 2002
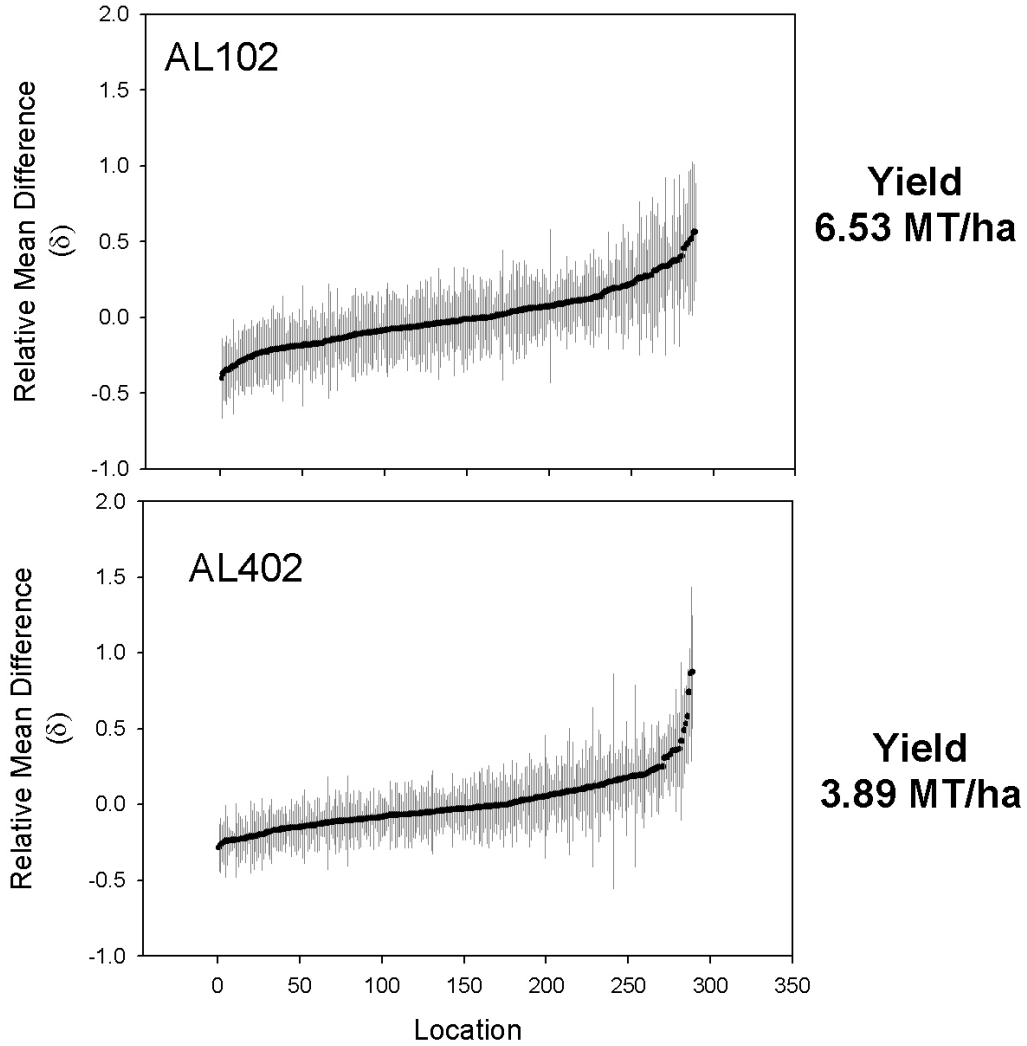
Figure 26. Ranked order of the relative mean difference and standard deviation of the surface soil moisture measurements during the 2002 growing season.

SURFACE SOIL MOISTURE 2002 - SEMI-VARIOGRAMS

The spatial relationships in the 2002 soil moisture data were tested using semi-variograms. The semi-variogram models for plot AL102 had ranges less than 6m, nuggets of 0.05 $(cm^3/cm^3)^2$, and sills between 0.071 and 0.153 $(cm^3/cm^3)^2$ (Figure 27). In the final four samples of the year, the magnitude of the nugget was more than 50% the magnitude of the sill. In the AL402 plots, the nugget value ranged from 0.008 $(cm^3/cm^3)^2$ to 0.03 $(cm^3/cm^3)^2$, the sill value ranged from 0.012 $(cm^3/cm^3)^2$ to 0.056 $(cm^3/cm^3)^2$, and the average range was 5.6 m (Figure 28). For the 2002 surface soil moisture data, the spherical semi-variogram models had shorter ranges, larger nuggets, and smaller sills compared to the 2000 semi-variogram models (Table 4).

The differences between the 2000 and 2002 semi-variogram models illustrates the changes in the spatial patterns of the surface soil moisture. The dry conditions in 2002 lead to patchy soil moisture that had less spatial dependence and more random variation than the 2000 growing season. In 2000, the highest moisture levels exhibited less spatial dependence; however, at the intermediate levels, the overall variance level was high and the spatial dependence was high.

SOIL TESTING - 2002 PLOTS

The non-nitrogen nutrient concentrations of the 2002 surface soil moisture plots were evaluated using relative sampling locations from the 2001 soil fertility sampling. Most of the nutrient values (pH, Mg, Ca, OM) were found to be very similar to the 2000 phase of the study (Table 3). The potassium levels differed slightly between the

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Figure 27. Semi-variance (cm³/cm³)² plotted versus lag distance for omni-directional sample (black line with dots) and fitted theoretical (blue line) spherical semi-variogram models for each day that the surface soil moisture data was collected in Plot AL1 during the 2002 growing season.

2002 Semi-Variograms of Surface Soil Moisture For Plot AL4 By Day
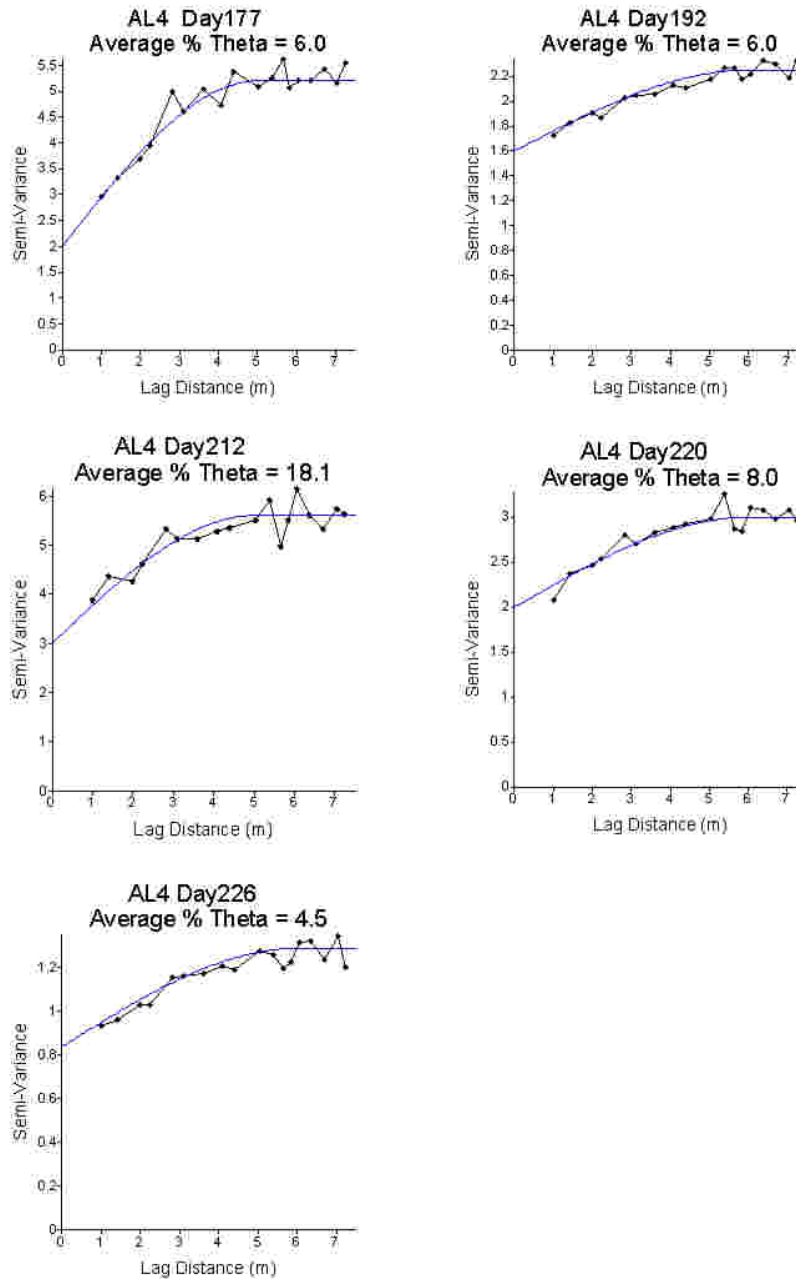
Figure 28. Semi-variance $(cm^3/cm^3)^2$ plotted versus lag distance for omni-directional sample (black line with dots) and fitted theoretical (blue line) spherical semi-variogram models for each day that the surface soil moisture data was collected in Plot AL4 during the 2002 growing season.

Table 4. Parameters of the theoretical spherical semi-variogram models fitted to the surface soil moisture data for the 2002 growing season.

Plot	Day	Nugget	Sill	Range (m)	Total Variance (nugget + sill)	Water Content (%)
AL1 2002	156	0.05	0.153	6	0.153	10.9
	177	0.05	0.105	1.5	0.105	12.5
	192	0.05	0.08	4	0.08	11.8
	212	0.05	0.098	1.5	0.098	12.4
	220	0.05	0.08	1.9	0.08	10.5
	227	0.05	0.071	2.2	0.071	6.3
AL4 2002	177	0.02	0.052	5	0.052	6
	192	0.016	0.022	6	0.022	6
	212	0.03	0.056	5	0.056	18.1
	220	0.02	0.03	6	0.03	8
	226	0.008	0.013	6	0.012	4.5

two experimental areas. The soil of AL402 was classified in the low potassium category, 40-94 kg/ha K_2O, while the soil of AL102 fell into the medium 95-179 kg/ha K_2O category. Texture analysis indicated a slight change in texture from sandy loam to silt loam between locations within the AL102 plot. The change in texture was probably as a result of the variability of the mapping unit in AL102. The soil test results indicated that the nutrient levels in AL102 and AL402 were similar to the soil conditions present in the 2000 plots.

Nitrogen concentrations in 2002 should have been sufficient to supply the corn crop. Similar to the 2000 growing season, pre-sidedress nitrogen sampling was used to adjust the application rate of nitrogen at the beginning of the growing season. Nitrogen should only have been limiting in cases where the growth and development of the corn crop exceeded the average production values.

YIELD DATA – 2002

The observed corn grain yields in 2002 were much lower than in the 2000 growing season. Yield data for plot AL402 was the lower than plot AL102 with a mean yield value of 3.89 MT/ha and a range of 0.19-5.77 MT/ha. In the AL102 plot, the observed yields had a mean value of 6.53 MT/ha and a range of 3.64-7.78 MT/ha (Figure 29). The 2002 yields were reduced in comparison to the levels observed in 2000; and in the case of AL402, the yields were less than the expected production values of the NRCS Beltsville Agricultural Research Center Special Soil Report (1995).

The yield semi-variogram for 2002 had an increased range and a lower variance than the 2000 yield semi-variogram. The range of the yield data in Section A was found to be 62 m (Figure 19) while the total variance (sill + nugget) observed was 69.0 $(MT/ha)^2$. The increased range and lower variance values of the yield semi-variogram can be attributed in part to the reduced corn production values. With reduced production, the spatial variability of the yield data is dampened and the spatial relationships are significant over greater distances.

FORECASTING OF SOIL MOISTURE USING ARMA

The 2002 surface soil moisture data collected during the experiment were used to evaluate the effectiveness of high-density soil moisture sampling and patterns of soil moisture in forecasting unknown soil moisture locations. The results of this study have indicated that patterns in soil moisture distribution are persistent during the growing season and that the spatial correlation of the surface soil moisture is less than 10m. Since high resolution surface soil moisture data can be time consuming and costly to acquire, it is not practical to collect these data for more than a few dates throughout the season. Instead of directly measuring locations, forecasts of soil moisture data could be performed using a soil moisture sample within 10 m and knowledge of historical surface soil moisture patterns. As a result, a set of high-density soil moisture measurement estimations could be constructed from a set of low-density samples.

Contour Plots of 2002 Yield Data for the Sampled Soil Moisture Plots
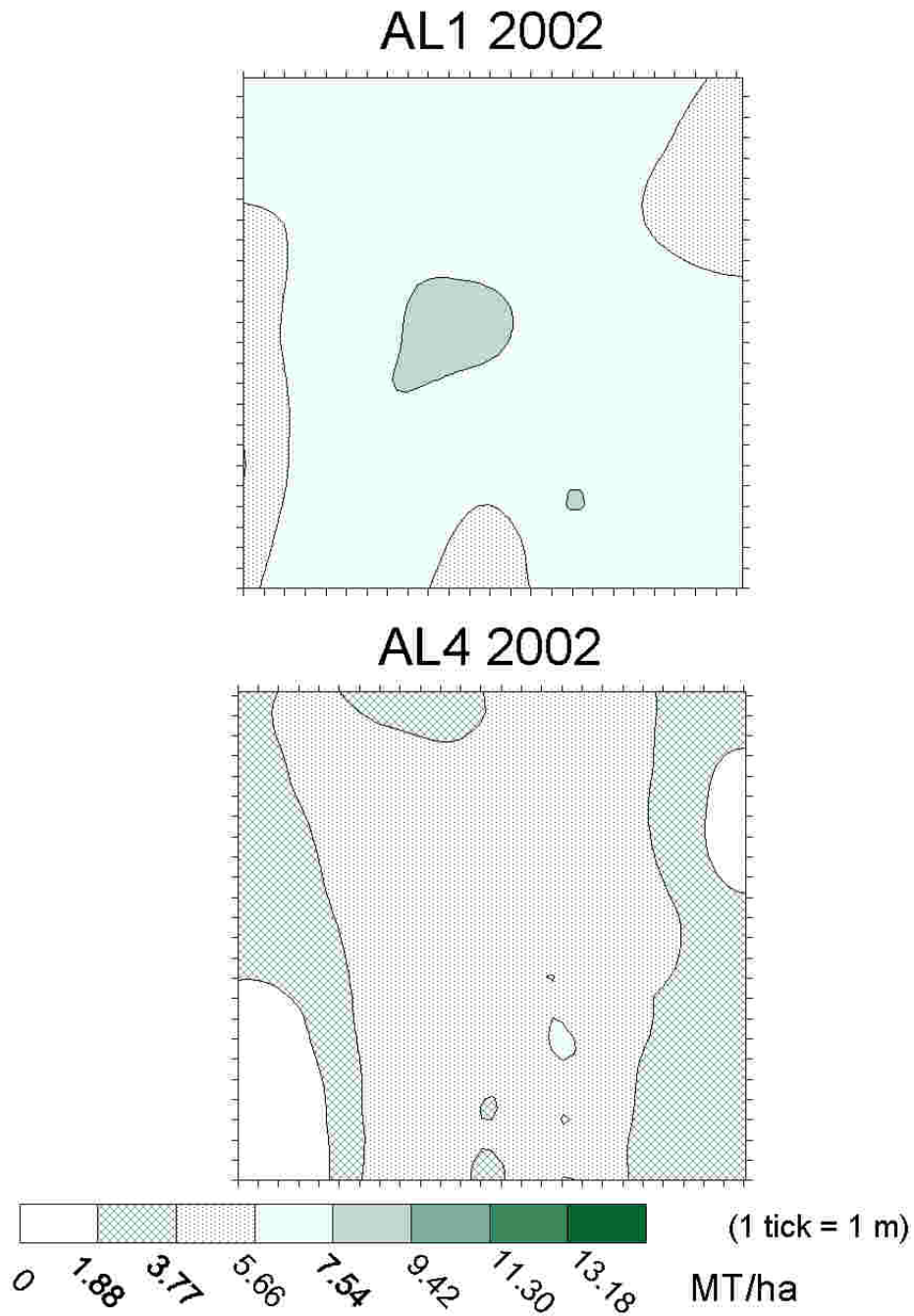
Figure 29. Contour maps of the corn yield data from plots AL402 and AL102 during the 2002 growing season.

Autoregressive-moving average models are capable of forecasting unsampled data and utilizing information from current and previously sampled input datasets. The ARMA models are used to evaluate and model autoregressive and moving average relationships that are contained within datasets such as the surface soil moisture. The patterns in high density surface soil moisture datasets may be quantified using an ARMA model. Combining the patterns of previously sampled datasets with a few current soil moisture samples could result in accurate estimates of high density soil moisture data.

Two designs were used to evaluate the ARMA forecasting for the AL102 and AL402 plots of the 2002 growing season. In the first set of estimations, the high-density soil moisture measurements were predicted using only points from the current dataset. In the second set of estimations, a combination of the current data and previously collected datasets were used in the predictions. In both cases, the estimations were performed by stretching out the two dimensional grid into a serpentine pattern for each plot on each of the sampling dates. The points selected as input data from the current dataset represented the previously sampled point or previously sampled two points from the serpentine pattern. In the second set of estimations, the input datasets included data from all of the previously collected datasets. Each of the previously collected datasets was tested for significance (α=0.05) before it was included in the final model; non-significant datasets were removed from the model. The final estimations of the surface soil moisture data for the 2002 plots represented combinations of the current and previously sampled data.

The results of the ARMA estimations using only the current data found that the predictions for the autoregressive (AR) parameters were similar for the AL102 and AL402 plots (Table 5). The range of the mean (μ) estimation in AL102 was from 6.33 to 18.93 cm^3/cm^3 while in AL402 the range was from 6 to 18.14 cm^3/cm^3. In both plots, the mean estimations followed trends in the soil moisture values. The first order autoregressive parameters (AR1) ranged from 0.2 to 0.37 cm^3/cm^3 in the AL102 plot. The driest date (Day 227) produced the highest (0.37 cm^3/cm^3) AR1 value. In AL402, the range of the first order autoregressive parameters was 0.21 to 0.35 cm^3/cm^3. The highest AR1 values in AL402 were associated with higher water contents, which indicated that the relationship between points diminished under dry conditions. The second order autoregressive parameters (AR2) for the AL102 plot decreased with lower water contents. For the AL402 plot, the AR2 values were not consistently statistically significant for inclusion in the ARMA model indicating that the AR2 term did not significantly contribute to predictions of the water contents for the plot. The fluctuations associated with the AR2 term in the ARMA model would not be considered unusual due to the fact that previous studies have found only the AR1 term to be consistently significant in small scale studies involving soil properties (Wendroth et al. 1992). The ARMA estimations for both plots exhibited similar patterns in the means and AR1 parameters but differed in the AR2 parameters indicating a potential difference in the longer distance AR properties of the plots.

The results of the second set of estimations provided an assessment of the correlation of the previously sampled datasets with the parameters determined by the ARMA procedure. Similar to the AR-only set of estimations, the results of the AL102 soil

moisture ARMA forecasts produced parameter estimations for the mean, error, autoregressive terms, and input datasets (Table 6). The parameter estimates for the AL102 means ranged from -2.42 to 17.97 cm^3/cm^3 while the error terms ranged from 3.13 to 8.88 cm^3/cm^3. Statistical tests on the estimations found that the first and second order AR parameters were significant for all of the sample dates except for the last date (Day 227). On Day 227, neither AR term was significant to the forecast procedure. The first order AR term parameters ranged from 0.14-0.19 cm^3/cm^3. The first order AR parameters were very consistent (0.19-0.20) in the early portion of the season (Day 172,177,192). The second order AR parameter ranged from 0.12 to 0.25 cm^3/cm^3. On all of the dates, the predicted means in the combined (AR and input datasets) set of estimations were considerably lower when compared to the AR-only set of estimations. The AR1 and AR2 values for the combination model set of estimations remained at or below the value found in the AR-only set of estimations. In the Day 227 forecast, which occurred on a very dry day, the AR terms were found to be insignificant to the model while 3 of the input datasets were found to be significant. The elimination of the AR terms from the model indicates that the variability found in the previous dataset was a better representation of the current data than a point sampled in a nearby position. The combined AR and input dataset forecasts of AL1 soil moisture values indicated that the AR parameters are reduced and potentially eliminated by sets of previously collected data.

Table 5.   Autoregressive parameters for soil moisture estimations within the AL102 and AL402 plots for each of the forecast dates. Estimations include the mean, error, first order autoregressive, and second order autoregressive parameters. The estimations for each date were determined using only the autoregressive portion of the model.

AutoRegressive Parameters

Plot	Forecast Date	μ	St Error	AR1	St Err	AR2	St Err
AL102	Day 172	18.93	0.25	0.2	0.057	0.26	0.057
AL102	Day 177	12.48	0.31	0.22	0.058	0.17	0.058
AL102	Day 192	11.86	0.3	0.27	0.058	0.2	0.058
AL102	Day 212	12.44	0.33	0.24	0.058	0.24	0.058
AL102	Day 220	10.53	0.30	0.22	0.058	0.23	0.058
AL102	Day 227	6.33	0.29	0.37	0.059	0.13	0.059
AL402	Day 192	6.00	0.13	0.21	0.062	0.14	0.062
AL402	Day 206	18.14	0.18	0.35	0.059	0.08	0.059
AL402	Day 212	8.82	0.3	0.31	0.058	0.26	0.059
AL402	Day 220	8.04	0.19	0.34	0.059	0.17	0.059
AL402	Day 226	4.54	0.11	0.26	0.059	0.17	0.059

The AR model and parameter estimations for the AL402 plot were calculated for 5 sampling dates (Table 7). Of the 5 forecasted dates, the AR model for AL402 contained 2 days where the 2nd order AR parameter was significant (0.05). The mean parameter estimation ranged from -0.08 to 15.7 cm^3/cm^3. Aside from Day 206, all of the mean estimations fell below 5. The error term ranged from 1.43-3.69 cm^3/cm^3. The 1st order AR parameter ranged from 0.12-0.26 cm^3/cm^3. The input datasets used in the AL402 forecasts included 1 to 4 previous samples. Similar to the AL102 plot, the combined model sets of estimations for the AL402 plot were characterized by lower parameter estimations for the AR models. On each of the sampling dates, the mean, AR1, and AR2 estimations were decreased by the presence of a previously sampled input dataset. As with AL102, the AR parameters in the Day 226 forecasting

date (i.e. date of driest soil conditions) were found to be insignificant while the input dataset remained significant. The contrast between the AR-only and combination model forecasts of the AL402 plot found that most of the variability was explained by previous datasets.

The combination model (AR and input datasets) set of forecasted data for AL102 was compared to the observed data each day to test the model performance in estimating soil moisture (Figures 30-32). Early season predictions for plot AL102 had very low R-squared values (0.151-0.259) indicating poor model performance. The AL102 forecasts for 177 and 192 overpredicted the 5-10% moisture measurements and under-predicted the 15-20 % soil moisture contents (Figure 30 and 31). In the late season AL102 forecasts, the R-squared improved to 0.483-0.648. The improvements in the R-squared values were attributed to improved predictions for the upper 25% and lower 25% of the data.

The combination model set of estimations for plot AL402 exhibited poor early season performance and improvements in the late season predictions (Figures 33-35). Similar to the AL102 forecasts, the R-squared values for the AL402 plot were very low (0.161, 0.225) for the early season measurements. The AL402 late season predictions improved (0.390-0.543), but the model forecast did not result in R-squared values at the level that was observed in the AL102 plot predictions. Although the average soil moisture conditions in AL402 (8.0%) were drier than AL102 (10.5%), the variability of the data appears to impact the model performance.

Table 6. Autoregressive parameters for soil moisture estimations of the AL102 plots for each of the forecasted dates. Estimations include mean, error, first order autoregressive, and second order autoregressive parameters. The estimation for each input dataset is also included. Input datasets that were collected after the date to be estimated were not included in the model and are indicated with a dash. NS indicates a non-significant factor in the estimation of soil moistures that was removed from the final ARMA model.

| Forecast Date | | AutoRegressive Parameters | | | | Input Dataset Parameters | | | | |
	μ	ERROR	AR1	AR2	Day 156	Day 172	Day 177	Day 192	Day 212	Day 220
Day 172	17.97	5.07	0.20	0.25	0.09	-	-	-	-	-
Day 177	2.17	8.88	0.20	0.12	ns	0.54	-	-	-	-
Day 192	7.81	6.64	0.20	0.15	ns	ns	0.32	-	-	-
Day 212	3.24	5.40	0.14	0.25	ns	0.13	0.54	ns	-	-
Day 220	0.96	3.14	0.16	0.16	ns	ns	0.22	ns	0.55	-
Day 227	-2.44	3.39	ns	ns	ns	ns	ns	0.10	0.17	0.51

Table 7. Autoregressive parameters for soil moisture estimations of the AL402 plots for each of the forecasted dates. Estimations include mean, error, first order autoregressive, and second order autoregressive parameters. The estimation for each input dataset is also included. Input datasets that were collected after the date to be estimated were not included in the model and are indicated with a dash. NS indicates a non-significant factor in the estimation of soil moistures that was removed from the final ARMA model.
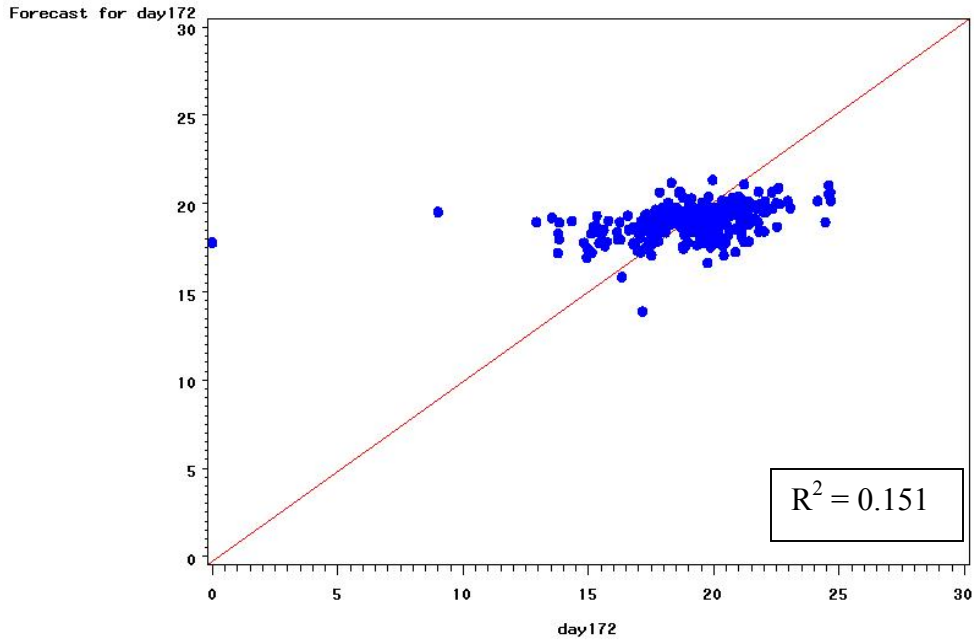
| Forecast Date | | AutoRegressive Parameters | | | | Input Dataset Parameters | | | |
	Mu	ERROR	AR1	AR2	Day 177	Day 192	Day 206	Day 212	Day 220
Day 192	4.53	2.02	0.13	0.13	0.24	-	-	-	-
Day 206	15.68	2.81	0.25	ns	0.23	0.18	-	-	-
Day 212	-0.09	3.70	0.24	0.22	0.35	ns	0.37	-	-
Day 220	1.96	1.44	0.26	ns	0.08	ns	0.11	0.42	-
Day 226	0.12		ns	ns	0.07	ns	0.07	0.12	0.21

AL1 Forecasts for the 2002 Growing Season

Forecast 172 — Day 156 p=2

$R^2 = 0.151$

Forecast 177 — Day 172 p=2

$R^2 = 0.232$

Figure 30. ARMA forecasted surface soil moisture versus observed soil moisture for the AL102 plot on day 172 and day 177. The order of the autoregressive function and the input datasets are listed above each graph.

AL1 Forecasts for the 2002 Growing Season

Forecast 192 — Day 177 p= 2

$R^2 = 0.259$

Forecast 212 — Day 172 177 p= 2

$R^2 = 0.483$

Figure 31. ARMA forecasted surface soil moisture versus observed soil moisture for the AL102 plot on day 192 and day 212. The order of the autoregressive function and the input datasets are listed above each graph.

AL1 Forecasts for the 2002 Growing Season

Forecast 220 — Day 177 212 p= 2

$R^2 = 0.648$

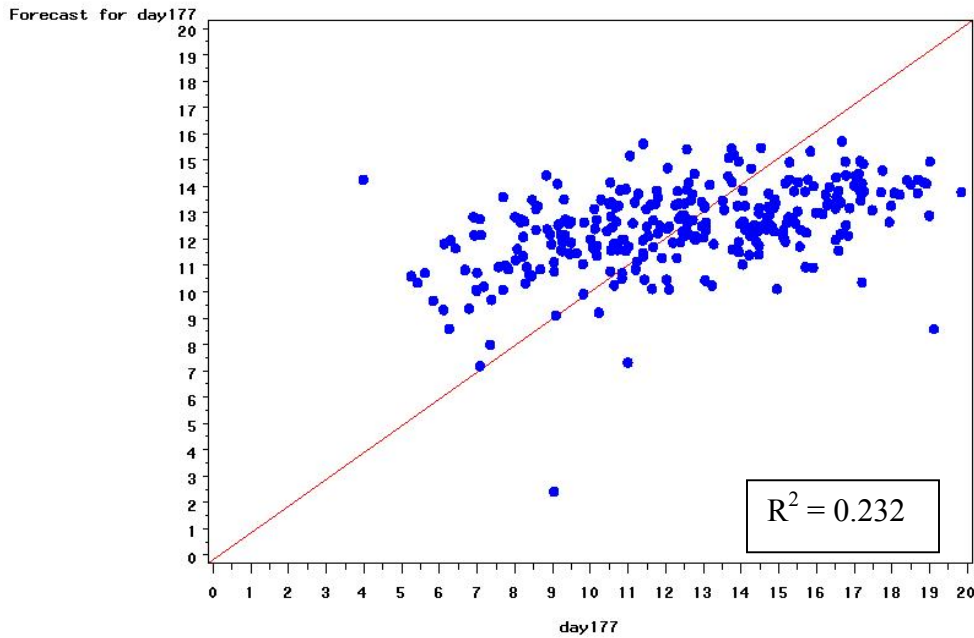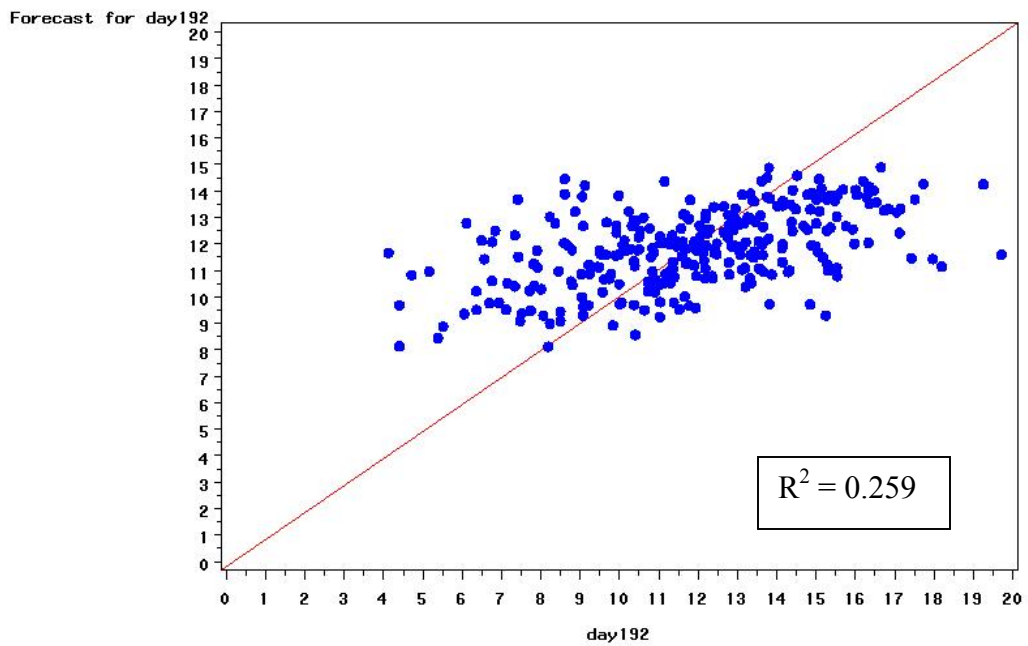## Forecast 227 — Day 192 212 220 p= 0

$R^2 = 0.569$

Figure 32. ARMA forecasted surface soil moisture versus observed soil moisture for the AL102 plot on day 220 and day 227. The order of the autoregressive function and the input datasets are listed above each graph.

AL4 Forecasts for the 2002 Growing Season

Forecast 192 Day 177 p=2

Forecast for day192

$R^2 = 0.161$

day192

Forecast 206 Day 177 192 p=1
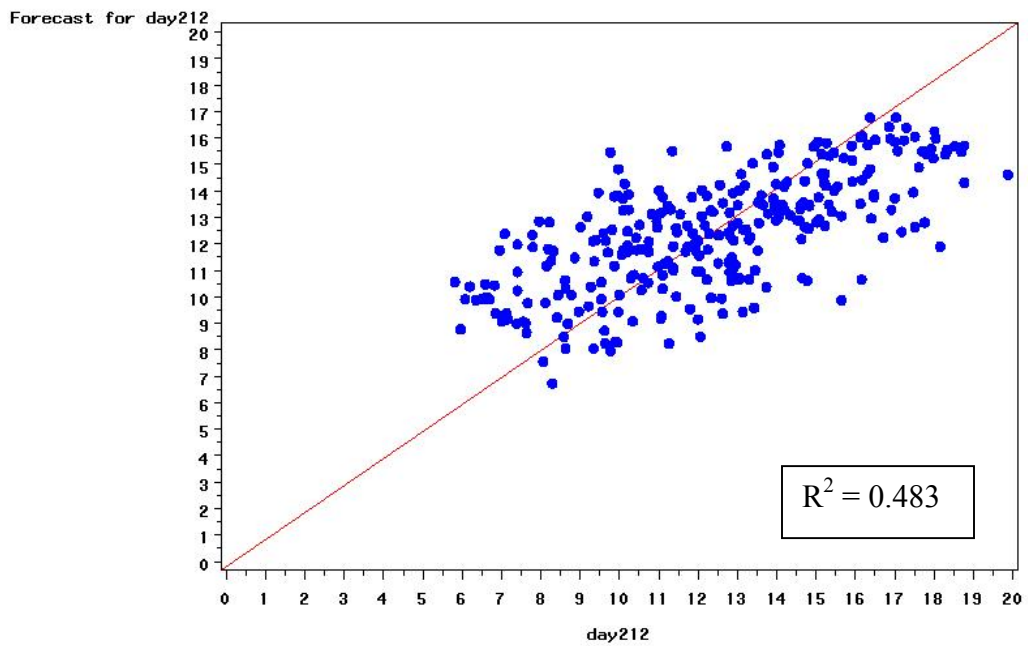

Forecast for day206

$R^2 = 0.225$

day206

Figure 33. ARMA forecasted surface soil moisture versus observed soil moisture for the AL402 plot on day 192 and day 206. The order of the autoregressive function and the input datasets are listed above each graph.

AL4 Forecasts for the 2002 Growing Season
Forecast 212 Day 177 206 p=2

$R^2 = 0.390$

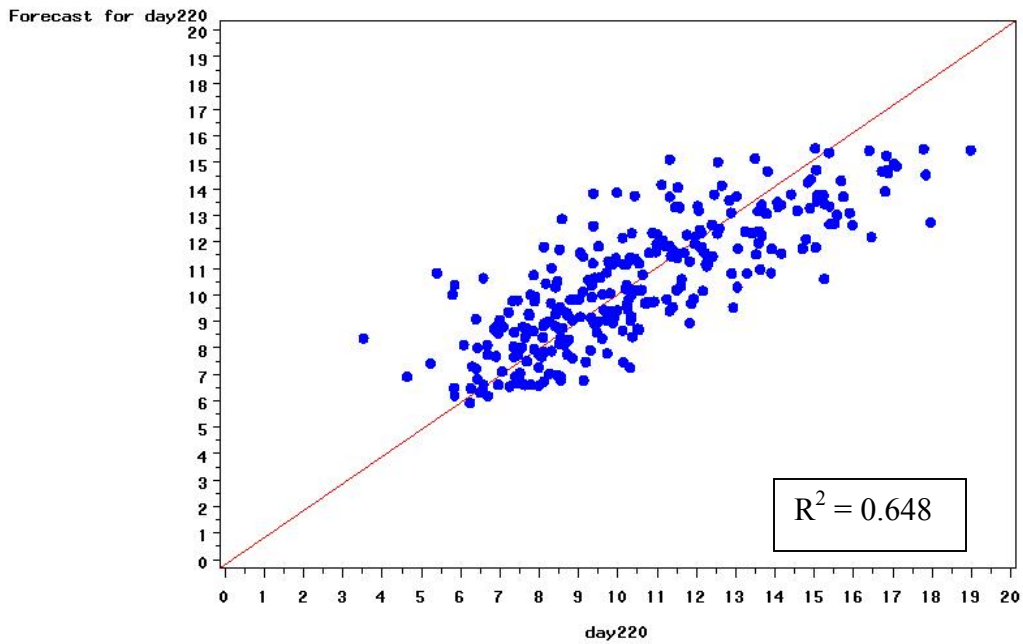## Forecast 220 Day 177 206 212 p=1
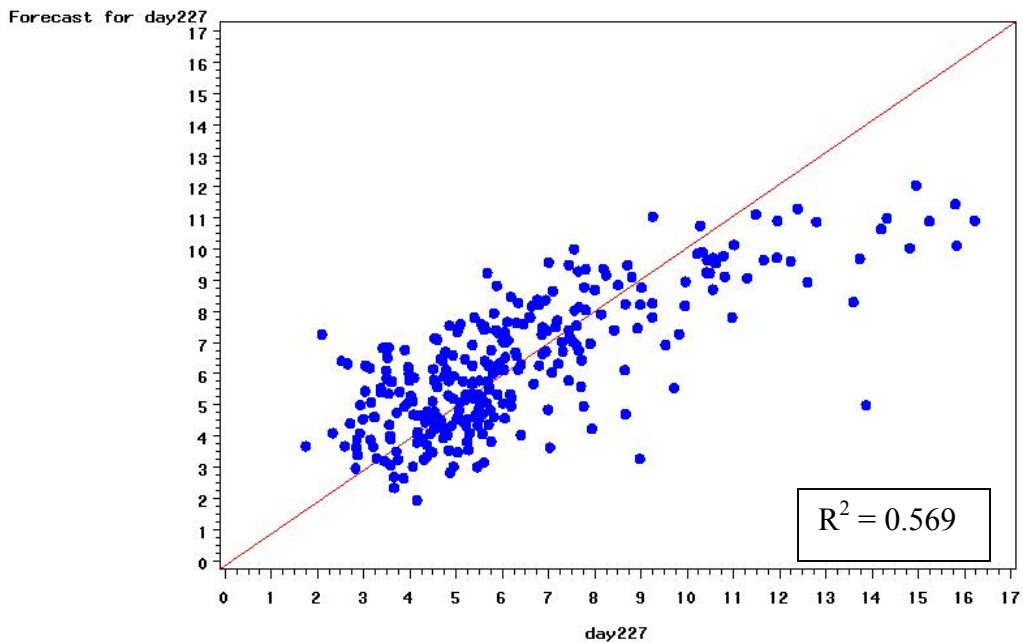

$R^2 = 0.543$

Figure 34. ARMA forecasted surface soil moisture versus observed soil moisture for the AL402 plot on day 212 and day 220. The order of the autoregressive function and the input datasets are listed above each graph.

AL4 Forecasts for the 2002 Growing Season
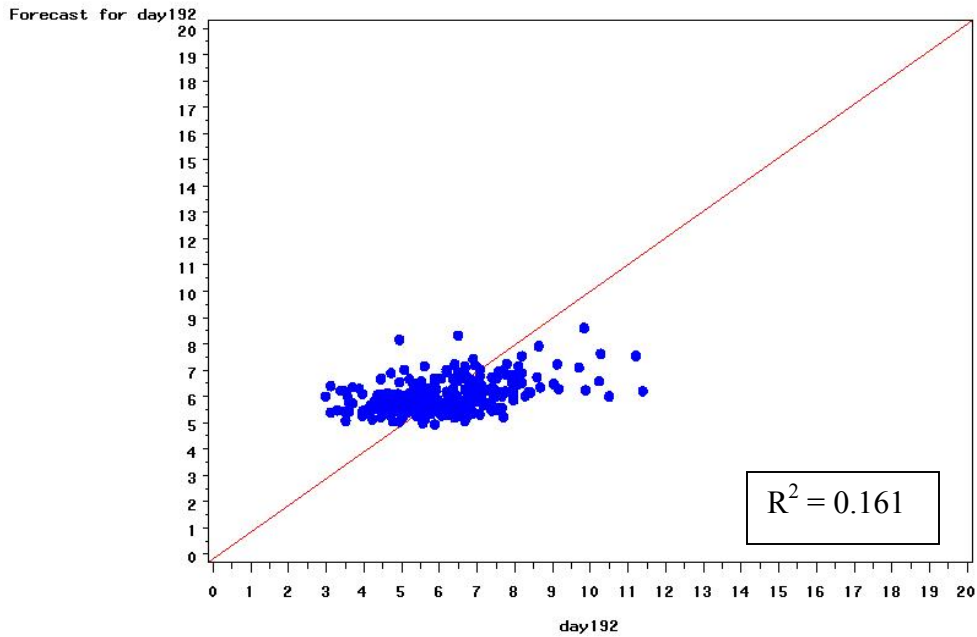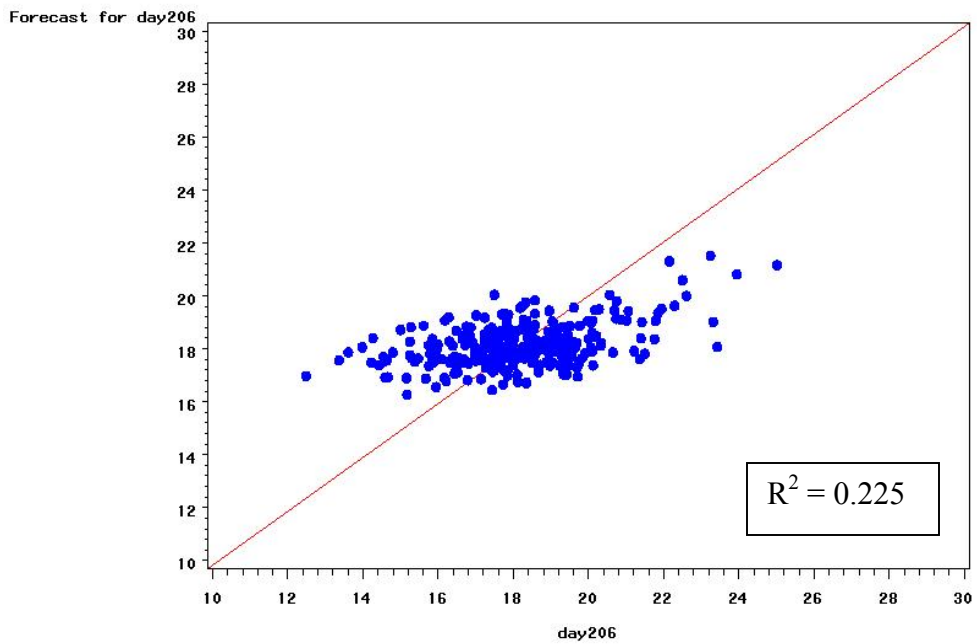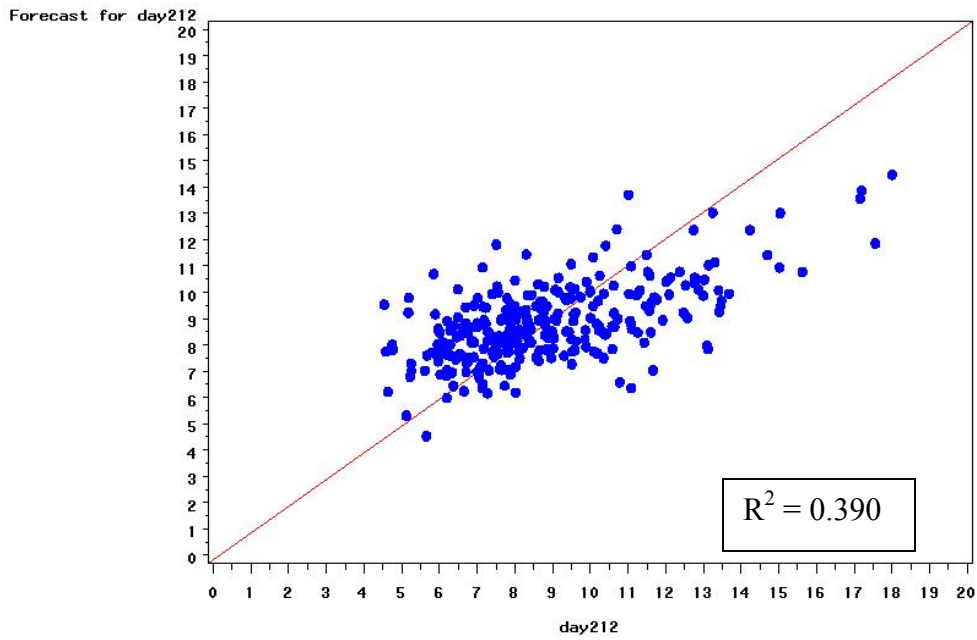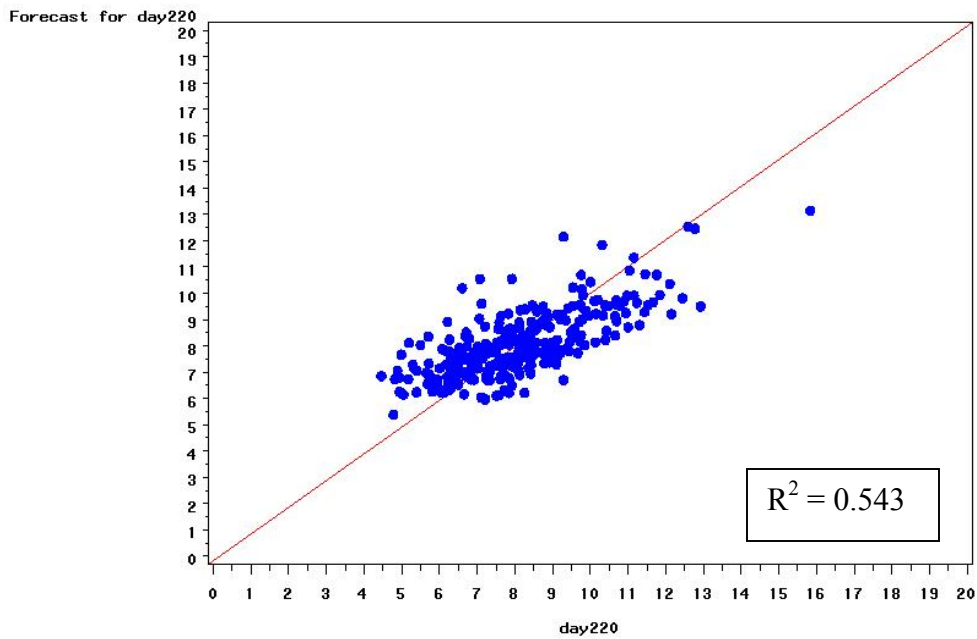
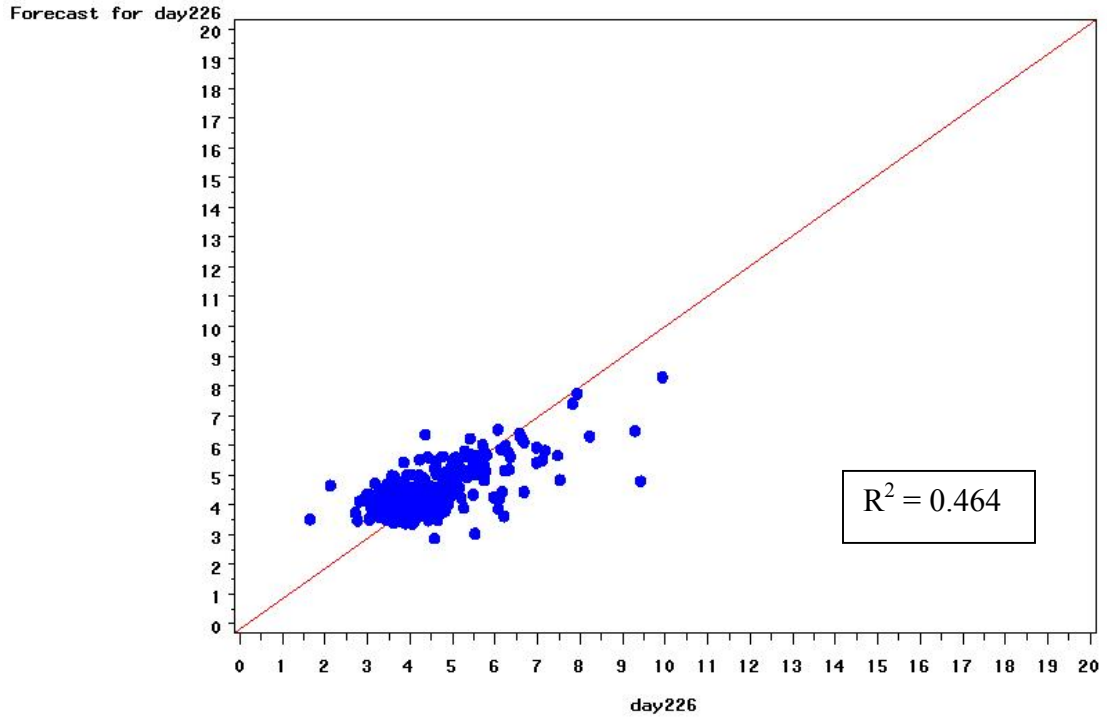## Forecast 226 Day 177 206 212 220

$R^2 = 0.464$

Figure 35. ARMA forecasted surface soil moisture versus observed soil moisture for the AL402 plot on day 226. The order of the autoregressive function and the input datasets are listed above the each graph.

The lower R-squared values indicate that the model did not simulate the variability in found in the dry conditions of the late season AL402 measurements as well as the observation found in the AL102 plot.

In Figures 36 and 37, it is evident that the forecasts with higher R-squared values were able to account for more of the observed variability within the soil water measurements. The variation of the soil moisture data appears to be accounted for by the input dataset portion of the ARMA forecasting procedure. Specifically, the addition of previously sampled soil moisture datasets appear to significantly improve the model performance compared to the addition of autoregressive terms for the current dataset. The autoregressive portion of the model does improve the estimations of surface soil moisture by 10-15% but the autoregressive parameter alone is unable to effectively account for the majority of the variability observed in the datasets.

SUMMARY

There were dramatic differences in growing conditions between the 2000 and 2002 growing seasons that were primarily a result of the difference in rainfall quantity and distribution. The 2000 growing season had 51% more rain during June, July, and August than the 2002 growing season.

The surface soil moisture levels observed in the plots were expectantly different between the 2000 and 2002 growing seasons due to these weather patterns. The mean observed surface volumetric soil moisture in 2000 ranged from 13% to 31%. The 2000 soil moisture conditions were considered optimal for plant growth,

AL102 Surface Soil Moisture Predictions

**Comparison of Observed and Forecasted
Surface Soil Moisture - Day 172**

$R^2 = 0.151$

**Comparison of Observed and Forecasted
Surface Soil Moisture - Day 220**

$R^2 = 0.648$

Figure 36. Comparison of early season and late season forecasts in the AL102 plot by individual locations. The observed data, the estimated, and the residuals for each location are plotted for each date.

AL402 Surface Soil Moisture Predictions

**Comparison of Observed and Forecasted
Surface Soil Moisture - Day 192**

$R^2 = 0.151$

**Comparison of Observed and Forecasted
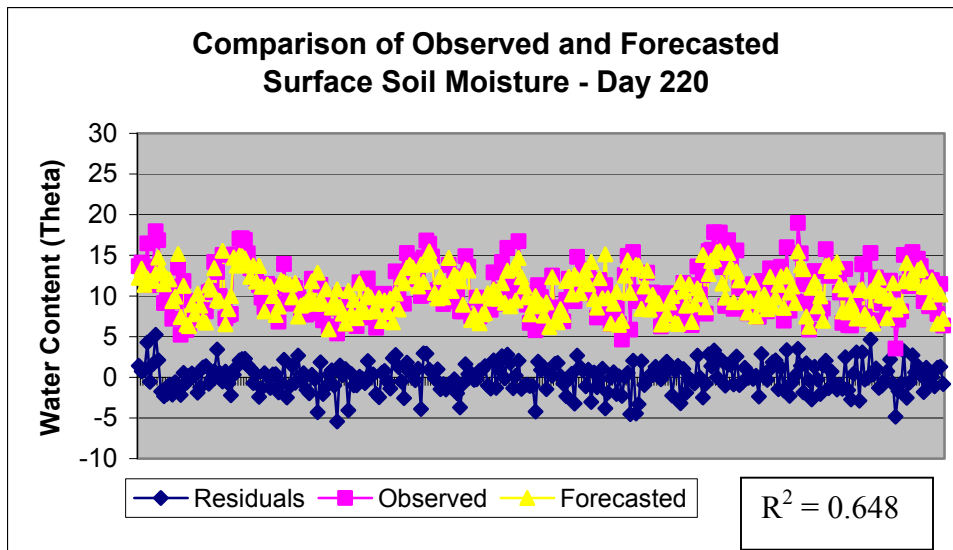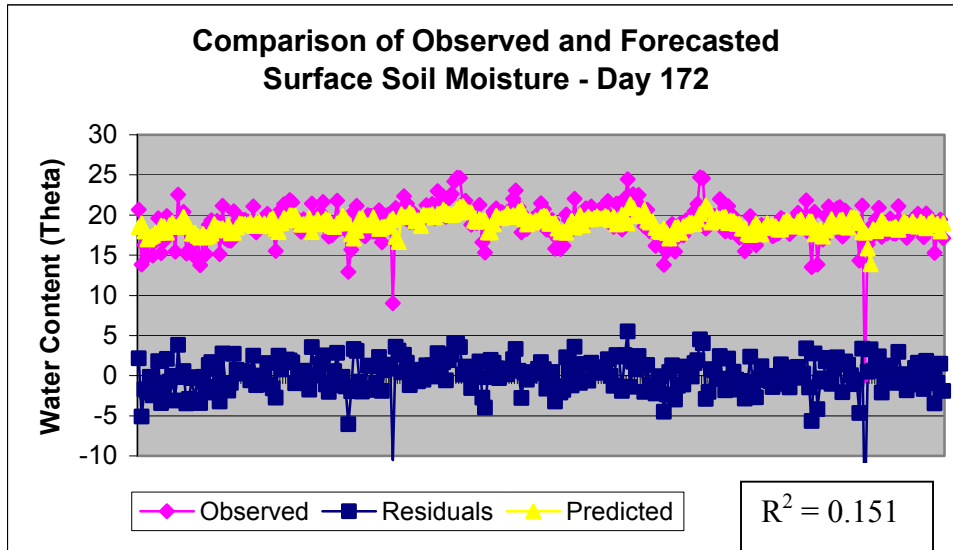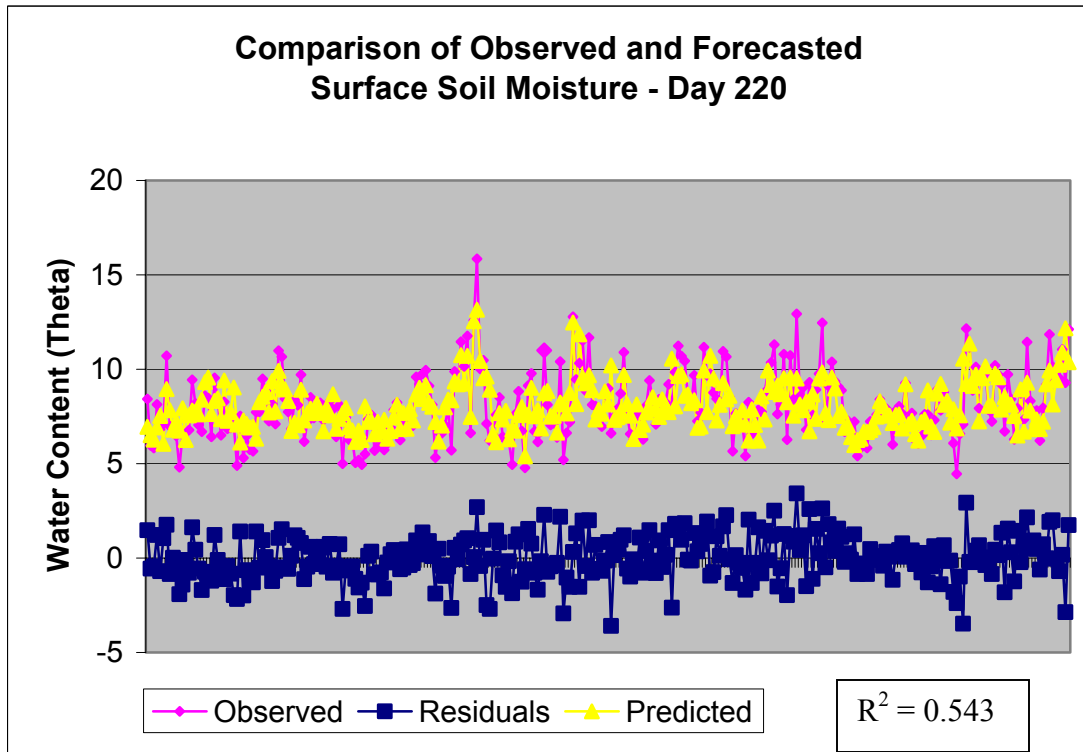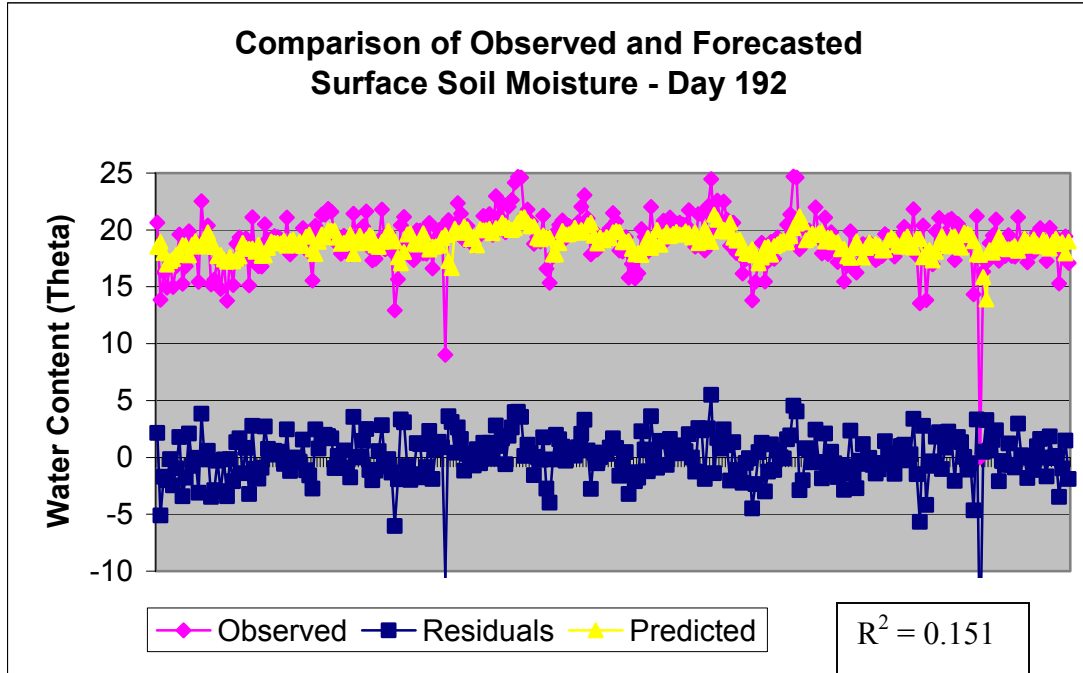Surface Soil Moisture - Day 220**

$R^2 = 0.543$

Figure 37. Comparison of early season and late season forecasts in the AL402 plot by individual locations. The observed data, the estimated, and the residuals for each location are plotted for each date.

with the exception of some short term saturated conditions. During the 2000 growing season, the highest mean water contents were observed in the AL1 plot (27.4%), followed by the AL3 plot (23.7%); the AL4 plot (21.7%) and AH3 plot (21.5%). In 2002, the range of the mean observed surface soil moisture data for the plots was 4.5% to 12.5% indicating that the soils remained at relatively low soil moisture values during much of the 2002 growing season. The AL102 plot had average plot surface soil moisture of 11%, while the AL402 plot had an average of 8.5%. The surface soil moisture values observed in sampling plots for the 2000 and 2002 seasons represented optimum and sub-optimum conditions of soil moisture for the growth and development of the corn crop.

The temporal patterns of soil moisture distribution were analyzed using contour plots of the differences between the observed surface soil moisture and the average plot surface soil moisture. The 2000 contour plots exhibited temporal patterns of wet and dry conditions that were persistent in plots AH3, AL1, and AL4 on observation dates throughout the season. The AL3 plot did not exhibit temporal patterns as distinct as the other plots. The lack of distinct temporal patterns was probably a result of the relatively low variances in observed surface soil moisture values across the plot. The patterns of 2002 soil moisture distribution demonstrated the temporal stability of surface soil moisture under drying conditions. The 2002 patterns of soil moisture distribution in the AL102 and AL402 plots started as a few large polygons and were gradually transformed into multiple smaller polygons. The corn rows appear to have impacted the change in the patterns of surface soil moisture as the breakup of the large polygons followed the north-south row orientation. The

patterns of relative soil moisture in the plots indicate that the temporal patterns of surface soil moisture under wet and dry conditions do not change rapidly over short time intervals.

The spatial patterns of the surface soil moisture for the 2000 and 2002 seasons were analyzed using theoretical semi-variogram models. Although precipitation was dramatically different for the two years; the semi-variogram analysis of the soil moisture content exhibited similar nugget, sill and range values for both years. The nugget value of the surface soil moisture semi-variograms decreased under wet conditions ($\theta > 25\%$) and increased under dry conditions ($\theta < 15\%$). Intermediate soil moisture conditions resulted in a gradual decrease in the nugget as the soil moved from dry to wet. Nugget variance in 2000 contributed as much as 50% to the total observed variance within a plot while in 2002 the nugget variance exhibited a maximum of 73% of the total observed plot variance. The sill values for the surface soil moisture semi-variograms were highest at intermediate soil moisture conditions (20-27%) and decreased at soil moisture values less than 15% or greater than 27%. The range of spatial dependence in the surface soil moisture semi-variogram was 5-10 m, depending on the soil properties and soil moisture conditions at the sampling location in the field. The range increased under wet conditions ($\theta > 27\%$) and decreased under dry conditions ($\theta < 15\%$) indicating that the spatial dependence of soil moisture decreased with decreasing water content within the field plots. The spatial dependence of the surface soil moisture and the characteristics of the theoretical semi-variogram model were found to be related the soil moisture levels and the soil properties of the sample location.

Soil test results indicated that the concentrations of the macro and micro nutrients required for corn crop growth and production in the 2000 and 2002 surface soil moisture plots were not significantly different between plots and should have provided sufficient plant nutrients to produce 6.28-7.53 MT/ha of corn. The nitrogen concentrations in the plots were tested and the sidedress application rates were adjusted to provide optimal available nitrogen for a corn crop goal of 6.28-7.53 MT/ha.

The corn crop yields observed in the 2000 and 2002 growing seasons were different for the two years. Yield production in 2000 exceeded the NRCS's 6.28-7.53 MT/ha average estimated production values for the major soil mapping unit within each of the 4 plots. During the 2000 growing season, the patterns of high surface soil moisture (i.e. above the mean) corresponded to areas of low corn production (<6.28 MT/ha) in the AH3, AL1, and AL3 plots. For 2002, the areas of the plot producing below the mean were also the locations where the soil moisture data was consistently below the mean. The differences in corn crop production between the plots and between years illustrated the strong effect of water content on yield found in the spatial patterns of yield.

The spatial variability of the corn yields for both years was evaluated using theoretical semi-variogram models. The semi-variogram for the corn yield data in 2000 exhibited a shorter range, higher nugget, and higher sill in the wet conditions than they did in the drier 2002 growing season. The higher variability of yield data in the wet year indicates that there is a larger range of spatial plant response compared to the spatial variability observed in the surface soil moisture. The shorter

range and higher variance observed in the 2000 data indicates that the spatial variability of the yield data was much higher than the spatial variability observed in 2002.

The estimation procedure for the 2002 surface soil moisture dataset provided an assessment of the potential use of high-resolution surface soil moisture datasets to estimate soil moisture conditions for future studies. Using the ARMA procedure, it was possible to estimate the variability found in the high-density surface soil moisture data by using a combination of nearby measurements of soil moisture combined with the spatial and temporal information available from previously acquired datasets. The early season estimations, which included only AR terms and a single, previous sampling date, resulted in R-squared values between 0.15-0.26. Estimations performed on dates later in the season, using several previous measurements and an AR term, resulted in improved R-squared values between 0.46-0.65. The majority of the improvement in R-squared values appears to be linked to the presence of the additional high-resolution datasets in the model. Adding and removing the AR term from the model resulted in a 10-15% change in the R-squared values. The high-resolution datasets collected throughout the growing season seems to account for a larger portion of the variability in the system than using information for points located in close proximity. Additional testing should be conducted to determine the benefits of the high-resolution datasets on soil moisture estimation for periods of time longer than this study.

The results of this study indicate that surface soil moisture exhibits temporal and spatial patterns over a range of water contents at short distances within a field.

The distribution and patterns of small-scale surface soil moisture is important for explaining portions of the spatial variability of crop growth and production as well as understanding the subsurface soil moisture properties. The properties of the spatial and temporal patterns of the surface soil moisture could be used to modify sampling strategies by focusing more samples into areas of high variability and removing some of the samples from the areas of low variability. Forecasting of soil moisture throughout the season could be performed using a combination of high resolution and low resolution datasets. More importantly, the temporal and spatial properties of the surface soil moisture might also be used to determine the resolution of future remote sensing sensors for accurate measurements of soil moisture over larger scales. Scientific examination of the spatial and temporal patterns of the surface soil moisture at small scales can help to explain the variability observed at small and possibly larger scales within an agricultural field.

FUTURE RESEARCH

Using the experiences of this research as a guideline, there are several factors/suggestions that could be used to improve future studies on subjects related to surface soil moisture. The suggestions address changes that could be made to the protocols for this study, methods to improve the study, and potential directions for future studies.

Several factors should be considered when deciding on the surface soil moisture sampling design for future studies. The layout and spacing of sample locations should be determined based on the research goals, the types of analysis, and the equipment/time limitations. The complete grid sampling design results in a set of

samples that is equally spaced across the sampling region. Certain types of analysis such as ARMA forecasting require these types of datasets. One advantage of the complete grid is that it is flexible for data analysis and can be sub-sampled to produce a nested dataset. On the other hand, the nested sampling design can be just as effective as the complete grid design for determining the spatial characteristics of an area. The advantages of the nested design are less sampling time due to fewer samples or more spatial coverage with the same number of samples. One of the drawbacks to this design is that it may need to be interpolated to a complete grid for certain types of analysis. The research goals and anticipated types of data analysis are some of the factors to consider when determining the sampling layout.

The method used for sampling the surface soil moisture would be recommended for future studies. PVC flags, labeled with a permanent marker, were used to identify and label the surface soil moisture sampling locations within the field. In this study, the coordinates of the corner flags of the plots were identified using a GPS sensor. The GPS coordinates were extremely helpful when overlaying the surface soil moisture data with other datasets such as the yield data or nutrient sampling. One of the concerns with the sampling method was the volume of the soil that was sampled. Longer probe lengths could be used to sample a larger volume of soil. In general, the method used to acquire the surface soil moisture data would be recommended for future studies.

Another suggestion for future work is to collect supplemental datasets with detailed information on soil properties and plant growth/development. Detailed soil nutrient maps, soil texture analysis, and sub-surface clay properties would provide

some beneficial information for this work. Ideally, the sampling densities for these datasets would be the same as the soil moisture data. Measurements on plant canopy size, plant growth stages, and population sizes would also be beneficial for analyzing the changes in the soil moisture contents. Remote sensing data, such as red, blue, and green spectrum data and thermal images, could have resolutions high enough to be used in this work. Below ground soil moisture sensors could be used in conjunction with surface data to provide a map of the soil water within the entire soil profile.

The future direction of this work seems to be closely associated with the advances in sensor technology and interpretation of the information. Advances in remote sensing technology should provide an affordable method to easily sample high-resolution surface soil moisture. In the meantime, high-resolution maps of soil moisture will be available primarily through point samples and interpolation. Research on the properties of small spatial areas within a field, the ability to manage different properties within these areas, and the ability to apply these management practices to a variety of locations should help evaluate the future application of high resolution surface soil moisture data to field sized areas.

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